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عنوان الرسالة / الأطروحة :

SENSOR PLACEMENT FOR DAMAGE DETECTION ENHANCEMENT IN
STRUCTURES DUE TO LOSS OF STIFFNESS

اعلن بأئني قد التزمت بقوانين الجامعة الأردنية وأنظمتها وتعليماتها وقراراتها السارية المفعول المتعلقة بأعداد رسائل الماجستير
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SENSOR PLACEMENT FOR DAMAGE DETECTION ENHANCEMENT IN
STRUCTURES DUE TO LOSS OF STIFFNESS

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**SENSOR PLACEMENT FOR DAMAGE DETECTION
ENHANCEMENT IN STRUCTURES DUE TO LOSS OF
STIFFNESS**

By

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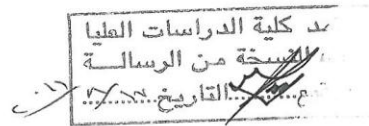
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**This Thesis was Submitted in Partial Fulfillment of the
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Master's Degree of Mechanical Engineering**

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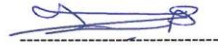
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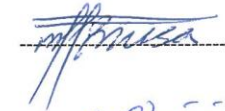
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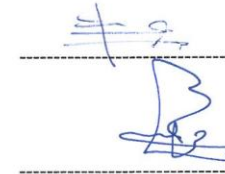
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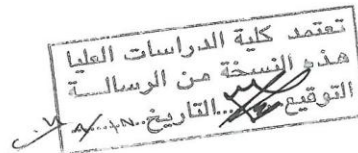
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To the most distinguished ...

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SENSOR PLACEMENT FOR DAMAGE DETECTION ENHANCEMENT IN STRUCTURES DUE TO LOSS OF STIFFNESS

**By
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ABSTRACT

An optimally sensor placement algorithm that exploits diversity of selected damage scenarios in structures is presented. The algorithm utilizes binary search based Particle Swarm Optimization (PSO) algorithm for finding the best sensors' configurations, and it employs Linear Matrix Inequality (LMI) for the damage detection process. The proposed sensor placement algorithm handled with partial measurement of structures modal data through modal expansion based on System Equivalent Reduction Expansion Process (SEREP) methodology. The results and algorithm effectiveness were successfully verified and validated using a simulated cantilevered beam application.

CHAPTER ONE

INTRODUCTION

The complexity of civil and mechanical engineering structures, continue to grow without any bounds. Dubai has just awarded the Italian architect David Fisher multibillions dollars tender to build a revolving tower. Each level in this tower has the ability to revolve by itself making the towers over all structure not fixed! These new trends in architecture engineering, demands an accompanying advancements in damage detection and structures health monitoring systems. Consequently, providing the civil, aerospace and mechanical infrastructure with an alarm of damage at its early stages will prevent harmful disasters. In this chapter a general overview on sensor placement for damage detection will be provided.

1.1 General Overview

Structural damage could be defined as change in material or geometry of a structure causing change in its dynamical behavior (mass, stiffness, strength, energy dissipation properties). Detecting and characterizing damage is referred as Structural Health Monitoring (SHM). Monitoring the healthiness of a structure has a great importance in maintaining the system safe and reliable. Structural health monitoring could be successfully implemented on civil, aerospace and mechanical infrastructure such as long span bridges, high-rise buildings, towers, aircraft parts (wings), space shuttles, rotors...etc (List of projects may be found in the survey done [54]).

Structural health monitoring possess a great interest to many researchers and as it is based on the comparison between the healthy case of the structure (pre-damage) and post damaged case, several algorithms were developed to detect damage in structures in its early stages. Fuzzy logic, neural networks, integrated based algorithms, genetic

algorithms, Generalized Minimum Rank Perturbation Theory (MRPT), linear matrix inequality, Particle swarm optimization are a sample collection of the techniques that were developed and used successfully for damage detection in civil structure and mechanical systems [2, 8, 33, 54].

1.2 Problem definition

Providing complete and precise dynamical measurements (collected via sensors) is vital for proper damage detection. These measured information are of main concern in the diagnosis of damage especially levels (2 & 3). Consequently, it is the configuration of sensors (type, location ...etc) that dictates the quality of the health monitoring technique results. Actually, a well-developed damage detection algorithm could be easily trapped into error if the measurements quality were poor (i.e. not noise wise). Hence, the problem boils down to find a structured methodology to select and place these sensors such that it exploits the capabilities of damage detection algorithms. Unfortunately, the number of sensors that one may utilize are limited (partial measurements) due to cost and practicality point of view. This adds up to the problem and makes the sensor placement a vital issue.

1.3 Motivation of the Current Work

This study provides the civil, aerospace and mechanical infrastructures with an early alarm of damage, consequently, preventing harmful disasters. On the other hand, proper placement of minimal number of sensors will be more efficient and economical for such systems, thus reducing the required huge cost, weight and duplicated information collected from sensors used. Finally, the sensor placement proposed

approach is tied closely with the damage detection techniques; hence, the damage detection will be enhanced.

The main objective of this work is to:

- provide a structured approach for sensor placement based on optimized search techniques
- Complement and enhance the damage detection techniques by analyzing priori the sensor locations
- To enable the damage detection algorithms to operate with minimal partial measurements and to compensate via the dynamical quality captured by the placed sensors.

1.4 Thesis Outline

The thesis was divided into five chapters. Chapter one gives a brief introduction on the thesis topic, defines the problem of the thesis and clarify the importance of the current work.

Chapter two was divided into three parts focusing on the main topics in the work, mainly: the damage detection problem, sensor placement techniques used by other researchers and finally a summary on the main optimization technique used in the thesis, which is Particle Swarm Optimization (PSO).

Chapter three was designed to provide the reader with a good explanation of the mathematics behind every technique used in every single step in the work. Starting from using Linear Matrix Inequality as a damage detection technique, to expanding the partial measurements collected via the sensors using System Equivalent Reduction

Expansion Process (SEREP) as an expansion technique and ending on the PSO technique that was used for sensor placement.

The sensor placement technique was tested by simulation of a cantilever beam set, chapter four defined the setup of the problem and introduced the simulation results collected using MatLab and discuss these results.

Finally, chapter five concluded the research that was performed and suggested some future work that may be done to improve the current technique.

CHAPTER TWO

LITERATURE REVIEW

The problem of small damage in large and mega structures could look like being a very simple problem, but when this damage propagate the damage problem will become of a main issue, especially when damage is not visible. The cost of repair and maintenance of damaged structure is definitely less than reconstructing the whole structure. During the last decade, several studies were held to study damage detection and many techniques were developed to place the sensors for an early alarm of damage. In this chapter a literature review on damage detection, sensor placement and the proposed technique particle swarm optimization will be provided.

2.1 Damage Detection

Damage in a structure or a mechanical system could be defined as a global change in the material or the geometric properties of the system, including changes to the boundary conditions and system connectivity. These changes will negatively impact either the current or future performance of the system. For instance, a small crack in a mechanical part will lead to change in its geometry which in turn will alter the stiffness, strength and dynamical characteristics of that in the place of the crack and its neighborhood. The part performance will be affected according to the size and location of that crack and the loads applied on the mechanical part. Even though a system's performance may not be affected immediately, but sooner or later as the crack size propagates the effect of damage on the performance of the system will surely appear [31].

Researchers and engineers have classified four damage detection levels. The lowest level is to diagnose if there is any damage (alarming). Once damage is

confirmed, one starts to locate this damage (localization). The next level is to quantify the severity of damage (extent). The last level deals with estimating the damaged structure useful life, which reflects how long it will take before the imminent complete failure takes place.

The first three levels of damage detection may be implemented using diversity of statistical models, such as the model based and response based approaches, while analytical models are needed to cover the last level of damage detection. Response based approaches require a proper selection of the sensor type, for instant, resonance frequency, mode shapes, mode shape slopes or curvature, strain energy, frequency response ...etc.[54]. Moreover, sensitivity of the sensor to small localized damage must be taken in consideration especially for detecting damage at its early stages.

A variety of researchers investigated damage detection techniques, some concentrated on frequency response in damage detection, while others investigated the topic using mode shapes, strain energy, damping or even by using artificial algorithms. An extensive survey work by Wang (2010) [56] summarizes many of these available damage detection techniques.

Frequency response in damage detection applications was considered as a sensitive indicator for damage. Wang, et al. (1997) [57] formulated a new damage detection algorithm using measured frequency response function data. The method was verified and validated by applying it to an experimental 3-bay plane frame structure. Different damages scenarios were inflicted on the beam. Numerical studies showed that the method was capable of identifying the locations and severities of damage within reasonable margins of error. On the other hand the presence of noise could affect the results of this method and minor damage could not be then detected.

Sampaio, Maia and Silva (1999) [49] expressed a method based on the absolute difference of frequency response function curvatures in both damaged and undamaged structures. This method was able to detect damage in a free-free beam structure, even in the presence of noise. This method and two other frequency response based methods were investigated by Maia, et al. (2003) [42] to find the difference between these methods and the mode shape based damage detection method. The methods were tested on a free-free beam; it was found that all methods with the exception of the mode shape based method were able to detect damage location.

Owolabi et al. (2003) [45] studied damage detection, by measuring the changes in the first three frequencies and their corresponding amplitudes. The experiment investigated with two sets of aluminum beams, a set was simply supported while the other was with fixed ends. Damage was applied as a crack in the beam varying in depth from 0.1 to 0.7 from the beams depth. It was observed that in both the first and second modes the fundamental frequency ratio (ratio of the natural frequency of the cracked beam to that of the uncracked beam) and the corresponding amplitude showed a downward trend as the crack depth ratio increased while the third mode showed a different trend.

Natural frequency is also an important dynamic property of any elastic system that could be a good indicator of damage. For instant any beam natural frequency depends on the equivalent modulus of elasticity or stiffness. So any shift in the systems natural frequencies could be considered as a damage indicator. Natural frequencies are relatively easy to measure, which make it popular in use for damage detection problems. On the other hand, natural frequencies in structures are measured in low modes, which make it unable to provide local information compared with the strain measurements about any change in the structure; it is more used to identify mere existence of damage

(alarming). Consequently, the location and extent of damage are difficult to be concluded about the system through the shift in natural frequencies alone [54]. However, if mode shape measurements are included then this problem will cease to exist.

As mentioned previously shift in natural frequency was popular in the uses of damage detection. Cawley and Adams (1979) [19]. They proved analytically and experimentally, that damage could be detected and quantified by a single point in a structure. The base of their method was to use the ratio of frequencies in two modes as a function of the damage locations.

Other researchers such as Banks et al. (1996) [14] concluded that natural frequency method depends on the geometry of the damage and that it could not be used for all types of damage.

Farrar and Jauregui (1998) [25] conducted tests on a steel plate girder bridge using natural frequency as a damage indicator, they concluded that due to the low sensitivity of frequency shift the need of either very precise measurements or large levels of damage increases, leading to the main conclusion that standard modal properties such as frequencies are poor indicators of damage.

Natural frequencies are effected by the environmental changes such as temperature and humidity, which will vague if this change is due to damage or it is only the effect of the environment. Wahab and De Roeck (1997) [55] investigated the effect of temperature on the modal parameters of a prestressed concrete highway bridge. They made their measurement in both spring and winter and the results showed the increase in temperature affected natural frequency of the bridge by a decrease of 4-5%. So it is

important to take into account the environmental effect when using frequency as a damage indicator.

Another dynamic property of any system is the mode shapes, and the majority of researchers suggested that it is far more satisfactory for detecting damage in structures rather than natural frequencies. Many methods were suggested to clarify the mode shape data. Many of these methods depended on the modal assurance criterion (MAC) Allemang and Brown (1983) [13]. The MAC suggests that if we suppose that (i) indicates the damaged mode shapes and (j) indicates the undamaged modes shapes and then find a correlation values between each mode shape of the damaged case with its corresponding reference in the undamaged case, then for undamaged structure it is expected to get the following:

$$MAC = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases} \quad (1.1)$$

Zhu and Xu (2005) [62] presented a sensitivity-based method for localization and assessment of damage in mono-coupled periodic structures. Both numerical and experimental results showed that the proposed method was able to detect either slight or severe damage, in either single or multiple locations, in mono-coupled periodic structures.

Moreover the derivative of modes shapes was used in many researches as damage indicator as it was found that they are more sensitive to damage than mode shapes themselves Zhu and Xu (2005) [62]. Mode shape curvatures can be obtained by differentiating mode shapes twice. Once one got the mode shape curvature the strain energy could be formulated as it is a function of mode shape curvature. Therefore, strain energy has been widely investigated as an indicator in damage detection, but it was

found by Abdalla (1999) [11] that strain information is localized in nature and does not offer global information about the structures damage.

For instant, Li et al. (2006) [40] presented a modal strain energy decomposition method for damage localization. The method was based on that the modal strain energy of every element in the structure is decomposed to two parts, one for the axial coordinates and the other for the transverse one. Both numerical and experimental work indicated that the axial damage indicator was able to locate damage occurring in horizontal elements, and that the transverse damage indicator was able to locate damage occurring in vertical elements. However, during the damage detection process the method generated false positive error, and it did not perform well estimating the extent of damage.

Choi et al. (2007) [21] presented a method that is based on system's modal strain energy called the modified damage index (MDI) method; which is applied it to a timber beam. The method was able to detect inflected damage scenarios based on experimental data. Moreover it was concluded that using a combination of high and low modes would provide better information in the case of multiple damages. But still the MDI method in that form was not able to catch the extent of damage (severity).

Expert systems were also used for damage detection problems, such as Genetic Algorithms, Neural Networks, and fuzzy logic. For example, Sazonov et al (2002) [51] presented a fuzzy logic expert system. It was examined on a Finite Element (FE) model of a simply beam. The system was able to recognize damages accurately.

Minimum rank Perturbation Theory (MRPT) by Mohammad Kaouk and Zimmerman (1994) [33] provided a closed form solution for the damage detection in

some structures. The closed form solution was tested on Nasa 8-bay structure and performed well for trusses.

Finally, Linear Matrix Inequalities (LMI) based techniques were used in damage detection by Abdalla et al. [3-7,8]. The LMI offered a unified approach for the detection process and provided an advantage in dealing with partial vibration measurements using LMI combined detection problem. Also, the same author investigated damage detection using alternating projection techniques that maybe used in model update as well as damage detection [12]. The techniques provided a mean to incorporate constraints such as sparsity, connectivity....etc.

2.2 Sensor Placement

Research on optimal sensor placement (OSP) has received much attention over the last two decades by the engineering community. The importance of (OSP) appears in several engineering applications, such as modal identification, control engineering and damage detection. Although, a large body of work has been addressed relatively well in the first two areas, a very small amount of applied experimental research has been done in optimal sensor placement for damage detection. The aim of (OSP) is to provide the identification process with the maximum meaningful data so that structural dynamic behavior can be fully characterized. This could only be performed if sufficient experimental information is available, which requires sensors to be correctly placed to capture as much dynamics as possible. Moreover, real structure dynamic behavior is only available if minimum amount of data is available. This in turn requires placing the minimum number of sensors with the most adequate information for the identification of the structure behavior. It is believed that optimal sensor placement can minimize the number of sensors, increase accuracy and provide robust system [2].

The present work focuses on determining the number and location of sensors in order to capture a data set that helps to provide vital information about damage in the structure. Different optimal sensor placement techniques were studied and tested on several large scale structures in order to detect damage in its early stages. Heo et al. (1997) [29] derived a kinetic energy based technique and applied it to real experimental data obtained from a model of an asymmetric long span bridge. The kinetic energy optimization technique provides a rough measure of the dynamic contribution of each candidate sensor to the target mode shapes. The kinetic energy method sensor placement procedure is similar to the Effective Independence (EI) method. The main difference is that the Kinetic Energy (KE) method objective is to find a reduced configuration of sensor placements which maximizes the measure of the kinetic energy of the structure rather than the determinant of the Fisher Information Matrix [36, 43]. Effective Independence (EI) was the base for several techniques for sensor placement in linear and nonlinear systems [18, 23, 32,39]. Li et al (2007) [38] combined both the Effective Independence (EI) and the Kinetic Energy (KE) methods by an iterative technique which ortho-normalize the reduced mode shapes repeatedly during iterations.

Li and Yam (2000) [41] used the spectral condition number of the Henkel matrix to find the optimal placement of sensors and the effect of noise was overcome by using the perturbation theory. A global search methodology was presented by Kripakaran et al (2007) [35], it was used to find the optimal placement of sensors for damage detection, and it was compared with the "greedy strategy" that was proposed by Robert-Nicoud et al. [48].

Genetic Algorithms were adopted to search for the optimal locations for the sensors. These algorithms were improved by Guo et al (2004) [26] using a crossover based on identification code, mutation based on two gene bits, and improved

convergence. On the other hand, Yan et al (2007) [59] developed an optimization procedure using Genetic Algorithm (GA) to place a piezoelectric sensor for damage detection in a composite wing box, using all differences in voltage signals decomposed by wavelet transform as a damage indicator.

Vibration response signals could also be used to optimize sensor locations, Li et al (2009) [39] proposed a criterion derived by the Representative Least Squares (RLS) method that depends on both the characteristics and the actual loading situations of a structure. It selects sensor positions with the best subspace approximation of the vibration responses from the linear space spanned by the mode shapes. Moreover eigenvector sensitivity based method was presented by Shi et al (2000) [53] to optimize sensor location and detect damage in structures using the collected information.

Several other techniques were used for the optimal sensor placement problem such as the generalized mixed variable pattern search (MVPS) [15], the effective independence method using the driving point residue (EFI-DPR), Eigen Vector Product (EVP), Non-optimal driving point based method, Variance method, model-based approach, Fisher Information Matrix Determinant FIM, Tabu search and Neural Networks, to enlist some of these techniques [22, 37, 43, 52, 58].

Recently Qiang et al (2010) [61] presented a new method for optimal sensor placement which is called Sensitivity Analysis (SA) method. It uses structural curvature mode shape changes due to stiffness changes (damages are simulated as stiffness reduction) to analyze the sensitivity.

Finally, Abdalla and Al-Khawaldeh (2011) [9, 10] provided an optimal sensor placement algorithms based on using the swarm optimization (PSO), which offer optimal sensor count as well as best sensor locations that exploits certain damage

scenarios. The following section will provide the reader with a brief literature review on the PSO topic.

2.3 Particle Swarm Optimization

Particle swarm optimization (PSO) went through a lot of developments since it was introduced in 1995. A wide range of researchers learned the technique and investigated improved forms of it, they also used the technique in many applications, and published many papers that studies the technique, its applications, and parameters and aspects of the technique. In this section we will give a brief literature review about the technique and some of its applications especially in damage detection and sensor placement.

For instant, Rao and Anandakumar (2007) [47] proposed a hybrid PSO algorithm by combining a self-configurable PSO with the Nelder–Mead algorithm to solve this rather difficult combinatorial problem of optimal sensor placement.

Perera, Fang and Ruiz (2009) [46] showed how (PSO) methods operate in damage identification problems based on multi-objective FE updating procedures taking into account the modeling errors. A comparison on the performance between (PSO) and Genetic algorithm was held experimentally.

Abdalla (2009) [2] used (PSO) to find the damage stiffness matrix that Eigen equation and satisfying the necessary symmetry, sparsity, positive definiteness, and damage localization constraints, he also held a comparison between both (PSO) and the alternating projection for detecting damage in a cantilevered beam.

Moreover Yu and Wan (2008) [60] carried out a comparative study on a single and multi-damage of a 2-story rigid frame, using an improved form of the (PSO)

algorithm by improving the inertial weight through adopting the sigmoid function. The results were satisfactory, where the improved form of the (PSO) algorithm was able to detect the location and extent of damage accurately.

Sandesh and Shankar (2010) [50] used a hybrid form of (PSO) algorithm and compared it with the pure (PSO) and Genetic algorithm, they applied it on Ackley and Schwefel multimodal benchmark functions and the hybrid (PSO) showed a superior in convergence and accuracy from both mentioned.

Fallahian and Seyedpoor (2010) [24] introduced an effective methodology by using (PSO) as a second stage to detect damage accurately (extent) when multi damage scenario is attended, using data collected from a first stage of searching for damage (potentially damaged elements) by using (adaptive Neuro-fuzzy inference system (ANFIS)).

Chen and Yu (2011) [20] investigated a new objective function for the optimization problems of structural damage detection. They compared it with the traditionally used objective functions such as natural frequencies and the MAC number, the new objective function was evaluated through numerical simulation of a 2-storey rigid frame. Improving (PSO) algorithm by using the new objective function made the algorithm powerful in detecting both location and extent of damage in both single and multi-damage scenarios, even with the existence of noise.

CHAPTER THREE

OPTIMAL SENSOR PLACEMENT FOR STRUCTURAL HEALTH MONITORING

Structural Health Monitoring (SHM) is the process of performing damage detection for aerospace, civil, and mechanical engineering structures using vibration signatures. SHM involves the observation of a system over time using an array of sensors to capture the dynamic response measurements, and due to the practical and cost testing limits, not all degrees of freedom (DOF) are measured, only a hand full of measurements are performed. Typically, there will be a need to expand the measured partial data collected by these sensors to build the full data for the required system. The expansion approach that is used in this work is based on System Equivalent Reduction Expansion Process (SEREP) [44]. Once the full data is readily established one may use any damage detection algorithm such as: LMI, MRPT, Fuzzy Logic,...etc [2, 8, 33, 39], the detecting algorithm used in this work was based on the popular Linear Matrix Inequality (LMI) [8]. The next logical step is to decide how many sensors to use and to estimate the optimal number and location of these sensors! In this chapter a searching technique that will be used to overcome this problem will be introduced, this search technique is based on the Particle Swarm Optimization (PSO) [2], Figure 3.1, shows a flowchart that describe the entire process, from collecting the data, expanding the measurements, detecting damage and finally, generating the number and location of sensors. The suggested approach on Figure (3.1) illustrates a sequential iterative optimization procedure for the sensor placement problem for an enhanced structural Health Monitoring (SHM).

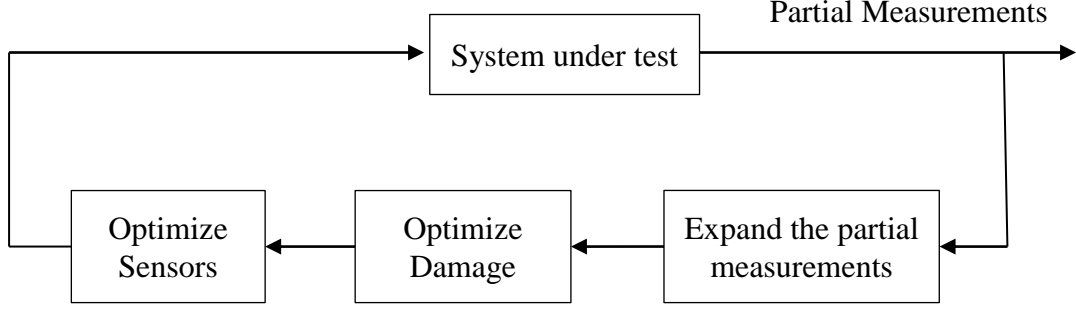


Figure (3.1): Sensor Placement for SHM

3.1 Damage Detection Problem

The basic idea behind the damage detection problem could be explained by considering an n degree-of-freedom (DOF) Finite Element (FE) model of a damped structure represented by the general equation of motion,

$$M\ddot{q} + C\dot{q} + Kq = 0, \quad (3.1)$$

where, M, C , and K are $n \times n$ analytical mass, damping, and stiffness matrices respectively, and q is an $n \times 1$ vector of DOF displacements. Assuming the FE model in (3.1) is an updated model of the structure (healthy); that is, the measured and analytical modal properties are in agreement (possibly through the use of a model updating procedure). Then the corresponding Eigen-equation of the FE model is given by

$$(-\omega_i^2 M + \omega_i C + K)v_i = 0, \quad i = 1, \dots, n, \quad (3.2)$$

where ω_i and v_i denote the i^{th} natural frequency and mode-shapes, respectively, of the healthy structure (i.e. before damage). Note that, for undamped and lightly damped structures the damping term in (3.1) maybe dropped out. Hence, one may rewrite the Eigen-equation in (3.2) in a matrix form as

$$KV = MV\Omega^2, \quad (3.3)$$

where $\Omega = \text{diag}(\omega_1, \omega_2, \dots, \omega_p)$ is a $p \times p$ diagonal matrix of eigen-frequencies and $V = [v_1, v_2, \dots, v_p]$ is an $n \times p$ modal matrix (modeshapes).

Now, assuming that damage in the structures is only represented as a loss of stiffness, and then based on a measured vibration modal data one needs to find the damaged stiffness matrix. Consequently, one needs to locate and find the damage extent of structures members [8], through the use of damage detection algorithms. It turns out that this is an inverse problem with many solutions. There are given measured vibration data before and after damage and one is asked to estimate the damaged stiffness matrix K_d . Figure 3.2 depicts the basis proposed damage detection process, as viewed by this work.

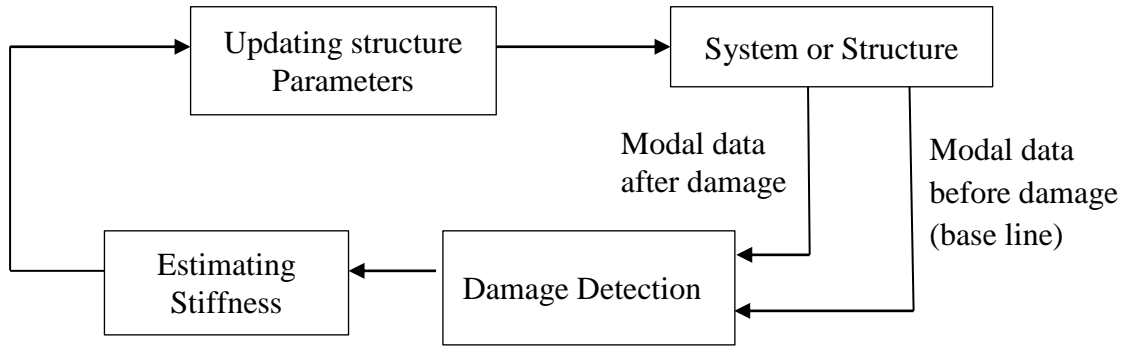


Figure (3.2): Damage detection using modal data

Literature search reveals two used categories of the approaches that are used for damage detection based on data measured. The measured modal data set could be complete or incomplete set (i.e. full or partial vibration measurements). Unfortunately, complete measurements of modal data are not feasible. Instead, one needs to deal with incomplete set of measurements. Hence, the damage detection algorithm needs to accommodate this issue. The available techniques are based on two methodologies: expand mode shapes then perform detection or reduce system then perform detection. In the expand then detect approach, the modal measurements full set is built through mode

shape expansion techniques [44], and then it is passed for performing damage detection. The main advantage here is the preservation of the original DOF of the structure, while in the reduce then detect approach the detection is carried out after reducing the structure. Hence, the main disadvantage is the lost structural connectivity (i.e. DOF's) making the localization of damage challenging; hence more work is needed to be done to reestablish the connectivity of DOF's.

3.2 Linear Matrix Inequality Based Damage Detection [1]

Linear Matrix Inequalities (LMI) is recently developed optimization techniques that are used widely in control theory. LMIs provide a unified controller design approach in optimal control, which are later solved numerically using interior point algorithms in a very efficient way [17]. A quick overview of the basic terminologies related to linear matrix inequalities (LMIs) and a brief list of some optimization problems based on LMIs will be presented in this section. The emphasis is restricted to the technical terms and LMI-based optimization methods that are relevant to this thesis. A detailed overview of the LMIs could be found in the monograph by Boyd and et al. [17].

3.2.1 Introduction

Definition 1 a linear matrix inequality (LMI) is an affine vector-valued function of the form,

$$F(x) = F_0 + \sum_{i=1}^m x_i F_i > 0, \quad (3.4)$$

Where $x_i = [x_1 \ x_2 \ \dots \ x_m]^T \in \mathcal{R}^m$ is the parameter vector, $F_i = F_i^T \in \mathcal{R}^{l \times l}$ are the given constant symmetric matrices, and $>$ denotes the positive-definite ordering of matrices; that is, $u^T F(x) u > 0$, for all $u \neq 0$ in \mathcal{R}^m .

The definition in (3.4) includes the constraints $A(x) < 0$ and $A(x) > B(x)$ since they can be rewritten as $-A(x) > 0$ and $A(x) - B(x) > 0$, respectively. The LMI in (3.4) defines a convex set $L = \{x: F(x) > 0\}$; that is, for any vectors x_1 and x_2 that satisfy (3.4), the convex combination $x_3 = \lambda x_1 + (1 - \lambda)x_2$ also satisfies (3.4) for any $0 < \lambda < 1$. Notice that multiple LMIs $F^{(1)}(x) > 0, F^{(2)}(x) > 0, \dots, F^{(j)}(x) > 0$ can be expressed as a single LMI,

$$\text{diag} \left(F^{(1)}(x), \dots, F^{(j)}(x) \right) > 0. \quad (3.5)$$

Therefore, we will make no distinction between a set of LMIs and a single LMI in control and structural analysis. Lyapunov inequality is a basic criterion for stability investigations which is the first known LMI (in 1890) [1],

$$A^T P + P A < 0, \quad (3.6)$$

where, $A \in \mathcal{R}^{n \times n}$ is the system matrix which is known and $P = P^T$ is a positive definite matrix. Consider a second order system $A \in \mathcal{R}^{2 \times 2}$. In this case, the symmetric P matrix is

$$P = \begin{bmatrix} p_1 & p_2 \\ p_2 & p_3 \end{bmatrix}.$$

Also define

$$P_1 = p_1 \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, P_2 = p_2 \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \text{ and } P_3 = p_3 \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}.$$

Hence, the Lyapunov inequality (3.6) can be expressed as an LMI constraint:

$$F(x) = F_1 x_1 + F_2 x_2 + F_3 x_3 > 0, \quad (3.7)$$

where, $F_i = -A^T P_i + P_i A, i = 1, 2, 3$. For the sake of notation, the LMI shown in (3.7) will be referred to as $F(x) > 0$. This shows that matrix variables can be cast as vector variables in the form of (3.4), so that the matrix variables will be used in all the formulations shown in this thesis.

3.2.2 Popular Problems Using LMIs [1]

A brief list of some common convex and quasiconvex LMI problems will be introduced in this section:

LMI Feasibility Problem

Consider the feasibility problem that consists of finding x_f such that $F(x_f) > 0$ or determining that the LMI is feasible. A natural example of that is finding $P > 0$ that satisfies the Lyapunov inequality in (3.6) or showing that there exists no such P .

LMI Eigenvalue Problem

The eigenvalue problem (EVP) is a convex optimization problem of the form

$$\begin{aligned} & \text{minimize } \lambda, \\ & \text{subject to } \lambda I - A(x) > 0, B(x) > 0, \end{aligned} \quad (3.8)$$

where, $A=A^T$ and $B=B^T$ that depend affinely on the optimization variable x .

An equivalent form of (3.8) hinges on minimizing a linear function subject to an LMI constraint; i.e.,

$$\begin{aligned} & \text{minimize } c^T x, \\ & \text{subject to } F(x) > 0. \end{aligned} \quad (3.9)$$

Here, $F(x)$ is a symmetric matrix that depends affinely on the optimization variable x and c is a real vector.

LMI Generalized Eigenvalue Problem

The generalized eigenvalue problem (GEVP) is a quasi-convex eigenvalue problem of the form

$$\begin{aligned} & \text{minimize } \lambda, \\ & \text{subject to } \lambda B(x) - A(x) > 0, B(x) > 0, C(x) > 0, \end{aligned} \quad (3.10)$$

Where, A , B and C are symmetric matrices that are affine functions of x .

An equivalent form of (3.10) is

$$\begin{aligned} & \text{minimize } \lambda, \\ & \text{subject to } A(x, \lambda) > 0, \end{aligned} \tag{3.11}$$

Where, $A(x, \lambda)$ is affine in x for fixed λ for fixed x and satisfies the monotonicity condition $\lambda > \mu \Rightarrow A(x, \lambda) \geq A(x, \mu)$.

For example, consider a linear time invariant system (LTI). The Lyapunov function condition,

$$\frac{dV(x)}{dt} \leq -2\gamma V(x),$$

For all the trajectories is equivalent to

$$A^T P + PA + 2\gamma P \leq 0,$$

Where γ is the decay rate (or largest Lyapunov exponent) $\lim_{t \rightarrow \infty} e^{\gamma t} \|x(t)\| = 0$.

The solution to this optimization problem can be found by solving the following GEVP:

$$\begin{aligned} & \text{minimize } \lambda, \\ & \text{subject to } A^T P + PA + 2\gamma P \leq 0, P > 0. \end{aligned}$$

3.2.3 Damage Detection Using LMI

Different LMI damage detection formulations were produced to overcome the partial measurement problem, for instant, LMI using Model Expansion [3, 7], LMI Hybrid Expansion-Reduction [3], LMI Combined Problem and LMI using Strain Measurements [11].

The detection algorithm that is implemented in this work is based on Linear Matrix Inequalities (LMI) [8]. Summary of the LMI damage detection formulation is provided here as a reference. Now, to take the advantage of the FE model connectivity, a parameter update formulation of damage detection can be developed that explores the element-by-element construction of the FE model stiffness matrix [1]. That is the identified structural stiffness matrix K_d can be decomposed as

$$K_d = \sum_{i=1}^n P_{di} K_i, \quad (3.12)$$

where, P_{di} are scaling parameters such that $0 < P_{di} \leq 1$ and K_i is the nominal elemental stiffness matrix that corresponds to the i^{th} element of the FE model and n is the number of elements in the FE model. Similarly, the healthy structural stiffness matrix K_h is given as

$$K_h = \sum_{i=1}^n P_{hi} K_i, \quad (3.13)$$

Hence, if $P_{di} \ll P_{hi}$ for some i , then the structure has been damaged at the i^{th} element, the parameter update problem now requires the solution of the following optimization problem

$$\begin{aligned} & \text{minimize } \|K_d - K_h\|, \\ & \text{Subject to } \|K_d V_d - M V_d \omega_d^2\| < \epsilon, \end{aligned} \quad (3.14)$$

The objective function in (3.14) can be simplified further by the substitution of the equations (3.12) and (3.13),

$$\begin{aligned} & \text{minimize } \|P_d - P_h\|, \\ & \text{Subject to } \|(\sum_{i=1}^n P_{di} K_i) V_d - M V_d \omega_d^2\| < \epsilon, \\ & \quad 0 < P_{di} \leq 1, \end{aligned} \quad (3.15)$$

where, $P_d = [P_{d1} \ P_{d2} \ \dots \ P_{dr}]^T$ and $P_h = [P_{h1} \ P_{h2} \ \dots \ P_{hr}]^T$ are the damaged and healthy vector parameters, respectively. Mathematically, the parameter update problem depicted in (3.15) is equivalent to the following LMI eigen-value optimization problem:

$$\begin{aligned} & \text{minimize } \text{trace}(S), \\ & \text{Subject to } \begin{bmatrix} S & (P_d - P_h)^T \\ P_d - P_h & 1 \end{bmatrix} > 0, \\ & \quad \begin{bmatrix} \epsilon^2 & Z(P_{di}) \\ Z(P_{di})^T & I \end{bmatrix} > 0, \end{aligned} \quad (3.16)$$

where, $Z(P_{di}) = (\sum_{i=1}^n P_{di} K_i) V_d - M V_d \omega_d^2$, and S is a symmetric slack matrix.

Derivation details maybe found in reference [62].

An estimation of the scalar noise parameter ϵ is needed to provide an accurate detection of damage in the presence of noise. Assuming that the damage natural frequencies $\omega_{di}, i = 1, \dots, r$ can be measured accurately, and that measurement noise mainly affects the measurements of the mode shapes $v_{di}, i = 1, \dots, r$, an estimate of the noise parameter ϵ_n can be obtained from the system eigen-equation as follows: Let V_d denote the noisy (experimental) mode shape matrix and \hat{V}_d be the exact mode shape matrix. Then,

$$K_d V_d - M V_d \Omega_d^2 = K \Delta V_d - M \Delta V_d \Omega_d^2 \quad (3.17)$$

Where, $\Delta V_d = V_d - \hat{V}_d$ and the eigen equation for the exact eigen data has been used. Hence, a bound for the left-hand-side of (3.17) can be computed as

$$\|K_d V_d - M V_d \Omega_d^2\| \leq \|K \Delta V_d\| + \|M \Delta V_d \Omega_d^2\|.$$

Assuming, $\|K_d\| \cong \|K\|$, that is the overall magnitude of the stiffness matrix due to damage is not changed significantly, and that $\|\Delta V_d\| = r \|V_d\|$ where the scalar r is the modeshape measurement noise level, an upper bound estimate for the noise parameter ϵ from the measured modal data is given as

$$\epsilon = r \|K V_d\| + r \|M V_d \Omega_d^2\|, \quad (3.18)$$

where, the scalar r is an estimate of the level of mode shape measurement noise. A practical estimate for the measurement noise level is given as $r=0.08-0.1$.

3.3 Damage Detection Using Partial Measurements [1]

Due to practical testing limitations, not all the DOFs of the structure are measured; instead, a small number of the most important DOFs are measured through a sensor placement process. To overcome the mismatch between the analytical model and

the experimental modal data, two approaches are currently employed: (a) modal expansion techniques that estimate the unmeasured DOFs that are then used in updating the full FE model [64] and (b) model reduction techniques in which the incomplete measured data are used in updating a reduced FE model [1]. However, it has been observed in many damage detection algorithms that modal expansion greatly increase the number of false positive in damage localization. Likewise, the use of model reduction tends to "smear" many damage location indications. These issues can mainly be tied to the usage of a healthy model based transformation matrix.

Most system modeling in structures are performed using the Finite Element (FE) method. The FE model generally consists of mass, damping, and stiffness matrices. However, the system damping is often poorly estimated because it is sometimes assumed to be a proportional damping type that depends on the mass and stiffness matrices, which turn out to be still useful in static analysis, load predictions, and dynamic response. The FE model approximates the continuous system with a finite number of elements, and the accuracy of this model representation increases as the number of elements increase. This trade off leads to the production of large system matrices. As a result, in performing model testing, the number of sensors that are used on the structure becomes a major issue to be addressed. Partial measurement becomes a necessity, and sensor placement optimization is used to capture most of the system dynamics within the operative frequency range. This mismatch between the analytical model and the experimental data must be resolved in order to update the FE model. The two apparent choices are either model reduction or model expansion.

Unfortunately, the partial measurements make the damage detection method more elaborate. The scheme that is used in this work is illustrated in Figure (3.3)

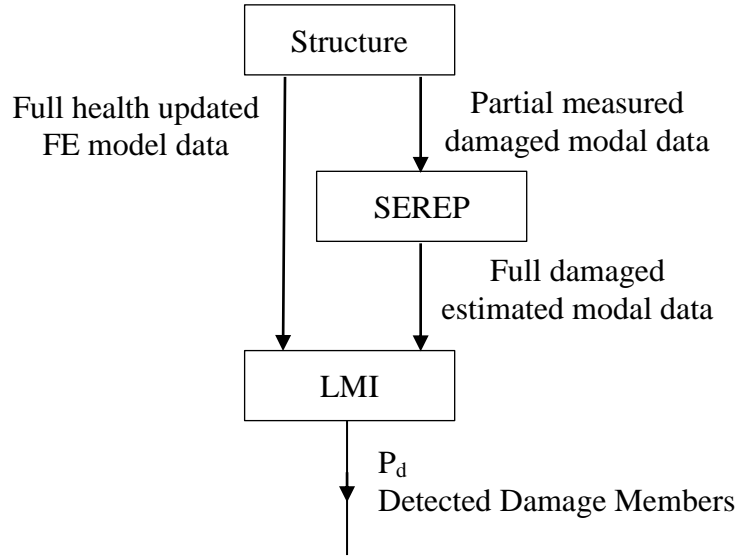


Figure (3.3): Damage Detection scheme

The following iterative damage detection scheme (Pseudo Code) is proposed to estimate the damaged parameters P_{di} .

Step 1 Expand modeshapes using System Equivalent Reduction Expansion Process (SEREP) [44] model expansion technique (will be discussed in the following section) and compute the expansion transformation matrix Q using equation (3.21)

Step 2 Compute ϵ using equation (3.18)

Step 3 Solve the LMI problem (3.16) for P_{di}

Step 4 Compute K_d using P_{di}

Step 5 Stop if the norm of the difference of two consecutive P_d estimates is small; otherwise, go to step 1

Our experience with this iterative scheme indicates that convergence occurs after few iterations. This iterative technique for the damage detection is used throughout this work.

Finally, please note that in this thesis, the measured degrees of freedom (DOFs) are referred to as the retained (r) DOFs and the unmeasured DOFs are referred to as the deleted (d) DOFs.

3.3.1 System Equivalent Reduction Expansion Process SEREP

All reduction techniques destroy the connectivity established by the FE model [16, 27]. In addition, the error from modeling and noise from measurements tend to smear out to every entry of the reduced matrices. Another alternative to model reduction is to expand the measured DOFs to include the unmeasured DOFs. Modal expansion solves the mismatch between the analytical model and the experimental data but suffers from sensitivity to noisy data. The expansion approach used in this thesis is based on the projection algorithms [28]. In this approach the measured data is projected to the FE model space using a transformation of the form

$$\begin{bmatrix} \phi_r \\ \phi_d \end{bmatrix} = Q \phi_r, \quad (3.19)$$

where, Q is the transformation matrix. A comparative study of the most used expansion methods could be found in references [28, 30, 63].

The expansion approach that is used in this work is based on System Equivalent Reduction Expansion Process (SEREP) [30] because of its effectiveness and ease of implementation. First one needs to partition the Eigen-equation matrix as follows

$$\begin{bmatrix} M_{rr} & M_{rd} \\ M_{dr} & M_{dd} \end{bmatrix} \begin{bmatrix} \Omega_{rr} & \Omega_{rd} \\ \Omega_{dr} & \Omega_{dd} \end{bmatrix} \begin{bmatrix} V_r \\ V_d \end{bmatrix} = \begin{bmatrix} K_{rr} & K_{rd} \\ K_{dr} & K_{dd} \end{bmatrix} \begin{bmatrix} V_r \\ V_d \end{bmatrix}, \quad (3.20)$$

then, a transformation matrix Q is constructed to carry out the expansion as follows

$$Q = (K_{dd} - \omega^2 M_{dd})^{-1} (K_{dr} - \omega^2 M_{dr}), \quad (3.21)$$

$$V_d = Q \times V_r, \quad (3.22)$$

The partitioned matrices are given as:

$$M_{rr} = M_h(r, r) , M_{rd} = M_h(r, d) , M_{dr} = M_h(d, r) , M_{dd} = M_h(d, d)$$

$$K_{rr} = K_h(r, r) , K_{rd} = K_h(r, d) , K_{dr} = K_h(d, r) , K_{dd} = K_h(d, d)$$

Once, these equations are coded in MatLab as a function it becomes easy to utilize, in this work a new MatLab function module was established and called expand. This function returns the expanded modal data that corresponds to the imputed partially measured model data. The results were thoroughly verified and validated of this MatLab function.

3.4 Optimized Sensor Placement for Structural Health Monitoring

In the previous section, a complete work is introduced on how to deal with partially measured damaged model data. Also, the damage detection proposed process was fully highlighted and discussed. At this stage we are ready to introduce the sensor placement technique.

The optimization part is carried out using Particle Swarm Optimization Binary based search technique, which is to be highlighted in the subsequent section.

3.4.1 Sensor Placement Methodology

An iterative technique is used to optimize the number and location of sensors on a structure. The objective of this optimization process was to place the sensors in such a way in order to exploit certain damage scenarios (hot spots).

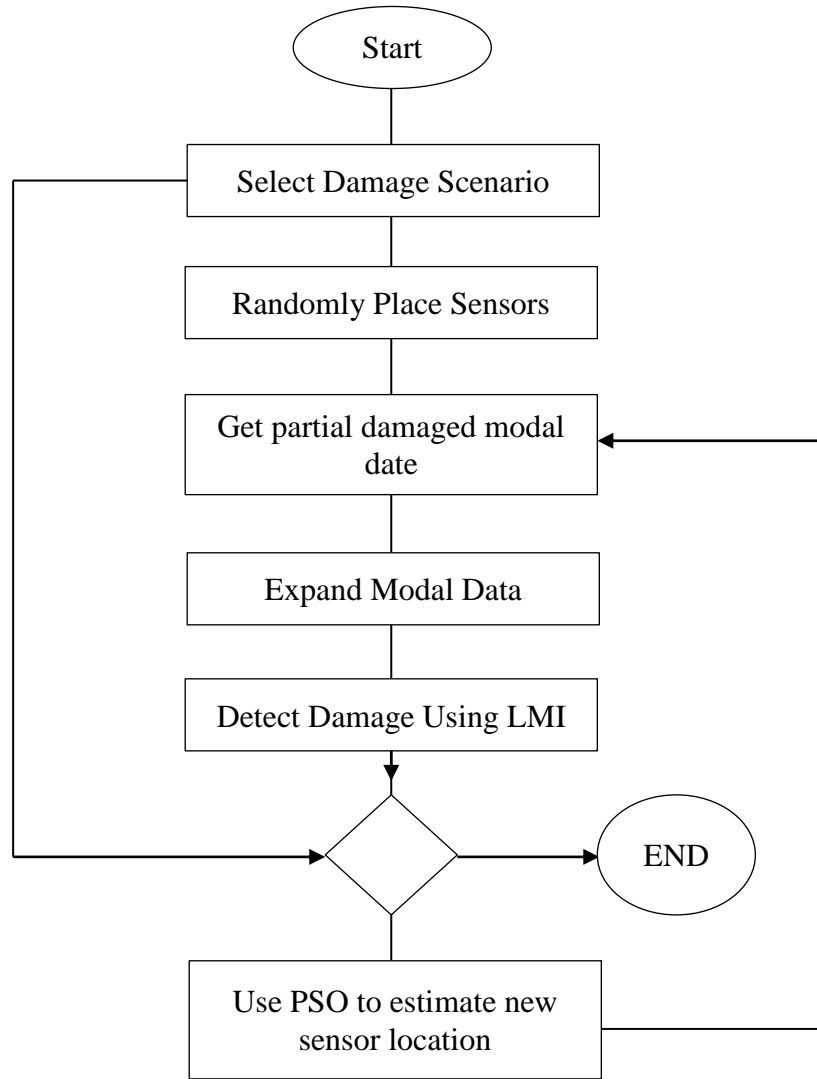


Figure (3.4): Sensor Placement Algorithm scheme

Figure (3.4) depicts the iterative algorithm that was used to estimate sensor locations for enhancing damage detection. Most of the blocks in the algorithm were fully discussed in the afore mentioned sections, except the Particle Swarm Optimization (PSO). The PSO will provide an optimized binary based searching procedure for updating the locations of the sensors. The fitness function that is used to provide performance checking mechanism for the PSO is based on comparing selected damage parameters (P_{ds}) and estimated damage parameters by the LMI (P_d). The Euclidean norm is used to compare the deviation of these damage vectors.

Now, binary search in PSO was used to overcome the difficulty in optimizing huge number of location parameters. Figure (3.5) depicts a cantilevered beam that is needed to be equipped with some sensors (say accelerometers).

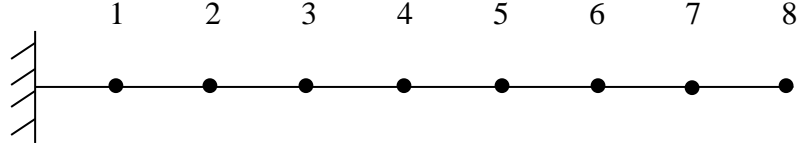


Figure (3.5): Binary Coded Sensor Location

The locations of the sensors may be decoded as one real parameter. That is to use binary number $\{0,1\}$ for designating the presence of absence of sensor. In this particular example the sensor location may be taken as:

Location = decimal $([b_1 b_2 b_3 \dots b_8])$ where, $b_i \in \{0,1\}$

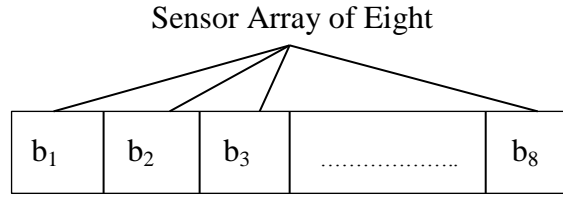


Figure (3.6): Binary Coding for PSO

This technique encodes every eight sensors in one decimal integer variable $[0,255]$. Figure (3.6) illustrates the binary concept.

Now, when the PSO starts its search quest it has the ability to turn on or off the sensor location (i.e. to have a measurement or not). The PSO does the search using one integer variable $L \in [0,255]$ for every set of eight sensors. The estimated PSO integer is then converted to binary to provide the corresponding partial measurement for the modal data. It turned out that this technique was very efficient for the PSO.

The next level is to discuss how the PSO perform its updates on the sensor locations.

3.4.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a search technique that is produced to fulfil the need of solving inverse problems. It is considered to be a population based stochastic optimization searching algorithm. It works for non-convex problems with minimum computational overhead. It was first been introduced 1995 [31].

The cornerstone of particle swarm optimization technique is the bird flock behavior, which is reflected from their social behavior. To have a good understanding of the PSO algorithm, imagine a flock of birds searching for food in some area, if each bird was searching individually the probability of success will decrease, while if each flock cooperated with the others then a global search would be facilitated.

The cooperation between birds in the same flock will result in raising the capacity of learning from the success of the neighbor birds, of course depending on the capacity of individuals and their ability of learning.

The Particle Swarm Optimization algorithm could be simulated as if each bird is referred to as a particle (a solution from the solution space), while the collection of particles is referred to as a swarm. Particles shall have positions and velocities that are updated frequently. Basically, each particle in the swarm tracks its location by means of two vectors; one accelerates the particle in the direction of a local best of its own and another towards a global best for the whole swarm (best of all the particle bests). These particle bests and the global best are measured against some form of a fitness function. Typically, the number of particles is between twenty and forty particles for good fast results. Figure (3.7) depicts an illustration of the PSO using bees social behavior.

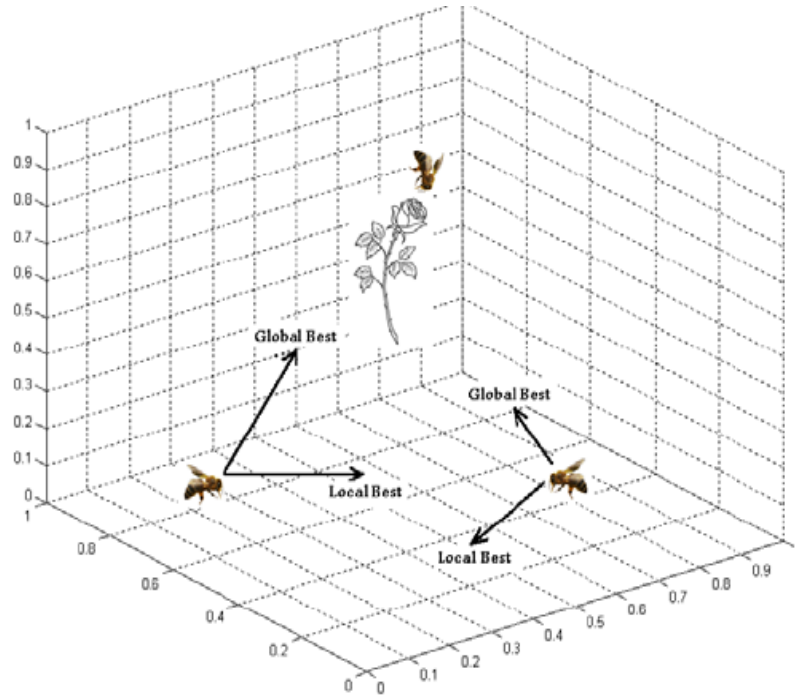


Figure (3.7): Swarm direction movement via two vectors [2]

Figure (3.8) lists the pseudo code for the PSO algorithm that is used to generate the sensor locations in this work.

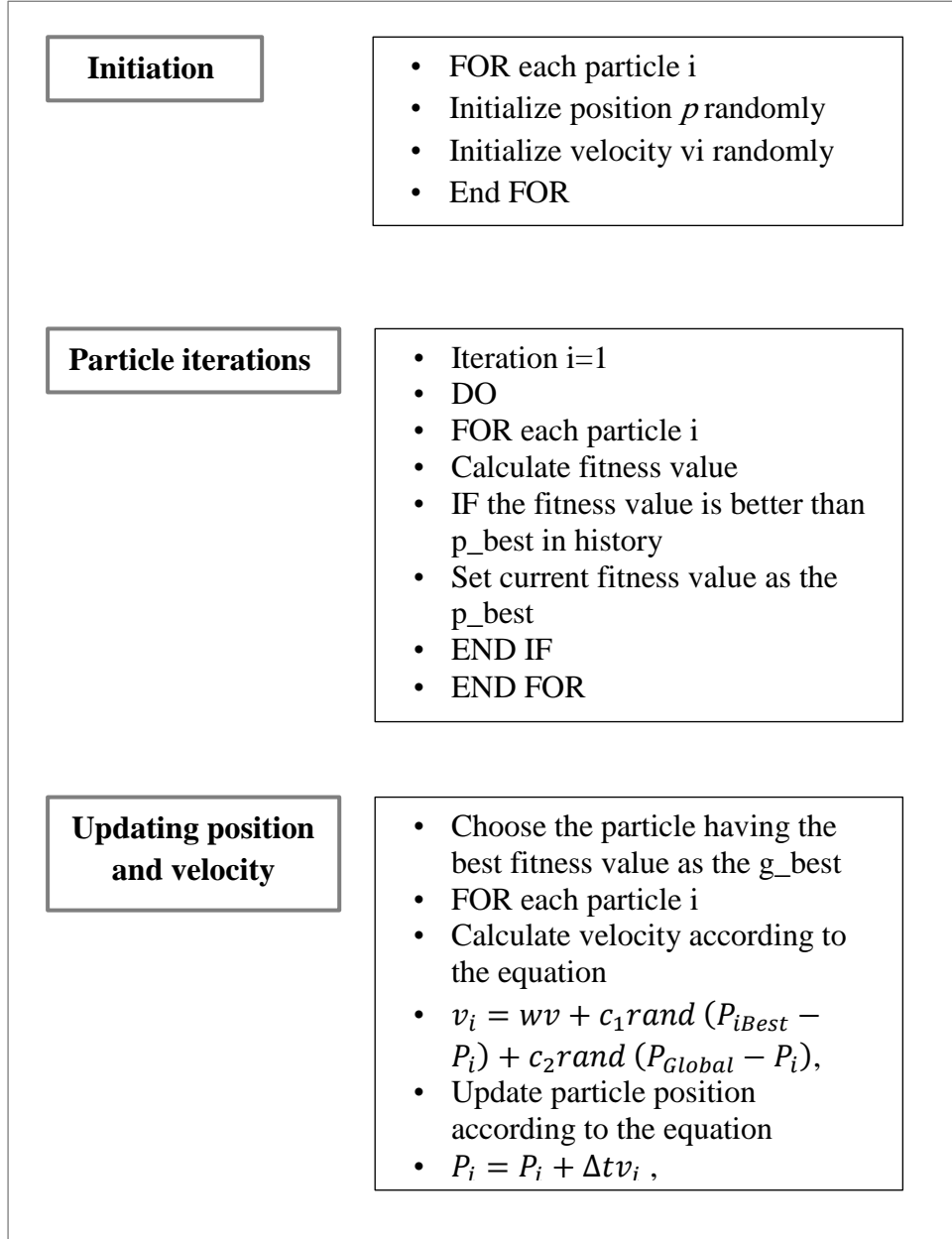


Figure (3.8): Particle Swarm Optimization Pseudo Algorithm

Please note that the fitness function used in the PSO binary search algorithm was based on comparing the selected damage scenario with the LMI detected damage parameters. Euclidean norm was used to exploit the deviation of the two vectors.

The sensor placement might seem computationally expensive, but on the other hand few iterations are only need to accomplish sensor placement for preselected damage scenario.

A good expression that may be used to update the velocities and position of the particles during the search is given in references [2, 34] as follows

$$v_i = wv + c_1 \text{rand} (P_{iBest} - P_i) + c_2 \text{rand} (P_{Global} - P_i), \quad (3.23)$$

where, w is a scalar that generates some form of momentum for the particle taken from the previous iteration. The constants c_1 and c_2 represent the emphasis toward the particle's best or toward the global swarm's best weighted by random terms. Typical values for these weights are within the interval $[0, 4]$, but good reported values in the literature of the scalars are $c_1 = c_2 = 2$. The local best is the best value of the solution attained by the particles and the global best is the best value of the solution attained by the whole swarm.

Finally, the advancement of a particle in any direction is controlled by the following simple kinematic equation

$$P_i = P_i + \Delta t v_i, \quad (3.24)$$

where, the Δt is the advancement in time and may be taken as one unit and P_i is the current location of the particle (i.e. solution).

This iterative algorithm starts with a group of random particles. New generations of particles are then updated until some form of convergence criterion (i.e. global best fitness) or a certain number of iterations is reached.

CHAPTER FOUR

CANTILEVERED BEAM APPLICATION

In this part, a cantilevered beam application will be used to verify and validate the effectiveness of the proposed sensor placement approach that is implemented in this work.

4.1 Simulated Damages

Consider a cantilevered beam made from Aluminum 6061, with $E = 6.9 \times 10^{10} \text{ Pa}$ modulus of elasticity and $\rho = 2.71 \times 10^3 \text{ kg/m}^3$ density, assume it is 0.90m long, 0.0508m wide and 0.0127m thick that is to be modeled, the beam was divided into seven elements as depicted in Fig (4.1). The first six elements are of length 0.127m and the last element is 0.13843m.

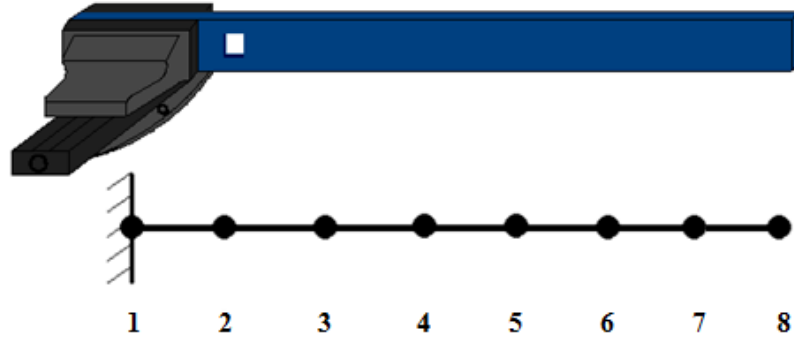


Figure (4.1): Cantilevered beam test bed as a simulated

A Finite Element (FE) model was performed to represent the healthy case, where the values for the mass, stiffness matrices could be found in appendix (A). This simulated test bed was used for creating diversity of damage scenarios for subsequent sections applications. The main objective is to find a good sensors locations and its

optimal number that exploit certain pre-selected damage scenarios from user's hot damage spots lists.

4.2 Simulation Results and Discussion

In this section the simulation of results for single and multi-damage are presented and discussed. Multi-runs of the simulation were done to collect the best sensor configuration that better represent the selected induced damage scenarios on the beam members.

4.2.1 Single Damage Results

The following table represents the optimal sensor configuration, with the minimum error that reflects the damage applied to the beam members in the single damage case. The table shows the fitness_gbest which represent the error percentage between the P_d of the damage scenario chosen and P_{de} estimated by the (LMI), Gbest represents the PSO output result for the optimal sensor configuration in decimal representation while the last column is the equivalent sensor configuration for the gbest in the binary form, where one denotes sensor present while zero denotes no sensor is needed.

Table (4.1): Single Damage Sensor Configuration

	Damaged Element	Error (%) (Fitness_Gbest) $\ P_d - P_{de}\ \times 100\%$	Decimal Sensor Configuration (Gbest)	Number of sensors used	Binary Sensor Configuration
1.	First	9.14	113	4	[1 1 1 0 0 0 1]
2.	Second	19.74	113	4	[1 1 1 0 0 0 1]
3.	Third	5.92	49	3	[0 1 1 0 0 0 1]
4.	Fourth	18.30	126	6	[1 1 1 1 1 1 0]
5.	Fifth	16.60	126	6	[1 1 1 1 1 1 0]
6.	Sixth	16.85	111	6	[1 1 0 1 1 1 1]
7.	Seventh	15.36	17	2	[0 0 1 0 0 0 1]

In the case of single damage, seven different scenarios were held; each scenario reflects 50% loss of stiffness on one beam element. The following figures represent the simulation results of these seven scenarios. The x-axis represent the element number and the y-axis represent the difference between P_h (healthy case (100% stiffness)) and P_{de} (resultant damage from LMI (reduction in stiffness)), where one reflect no damage and zero fully damaged.

Example:

A damage on the second element resulted in reduction in the beam's stiffness of 40%, so P_{de} , P_h and the difference between ($P_h - P_{de}$) will be represented as follows:

$$P_{de} = \begin{bmatrix} 1 \\ 0.6 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \quad P_h = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \quad P_h - P_{de} = \begin{bmatrix} 0 \\ 0.4 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

The simulation results will be represented in the same manner, see figure below.

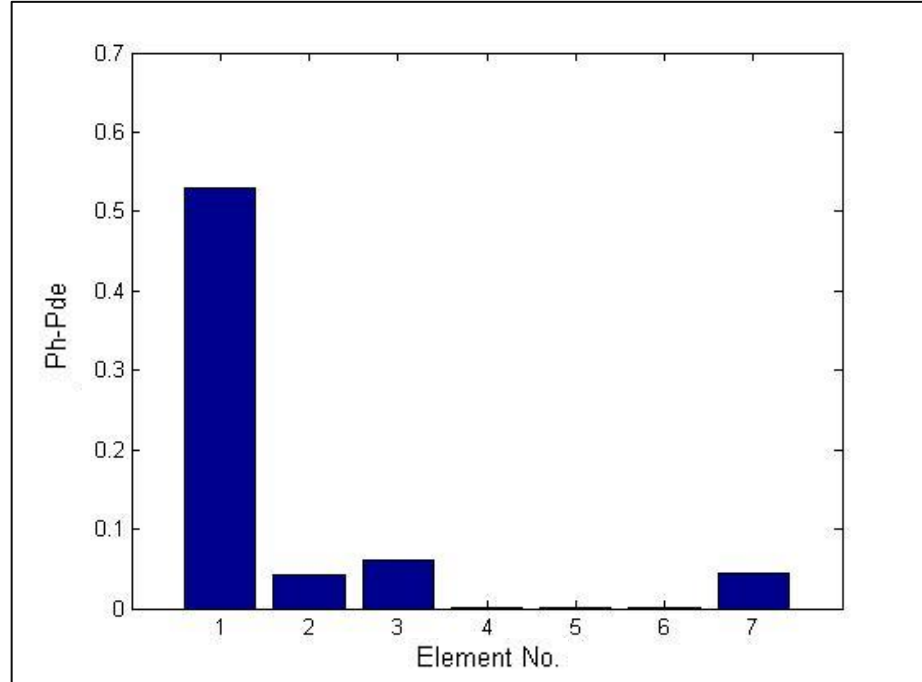


Figure (4.2-a): Root member simulated damage

An induced damage (crack) at the root element that leads to a loss of the beams stiffness of 50% requires at least four sensors to be detected correctly in the case of the cantilevered beam used in this work. Executing the Particle Swarm Optimization algorithm for the damage detection enhancement reveals that the best sensors configuration was [1110001]. Now, if one uses the generated sensor configuration to produce the corresponding frequencies and mode shapes, expanding the unmeasured DOF's, then followed by applying the Linear Matrix Inequalities (LMI) damage detection method to detect the induced damage, the estimated damage will be as depicted by Fig.(4.2-a). Hence, such a sensor configuration exploits damages done on the first element.

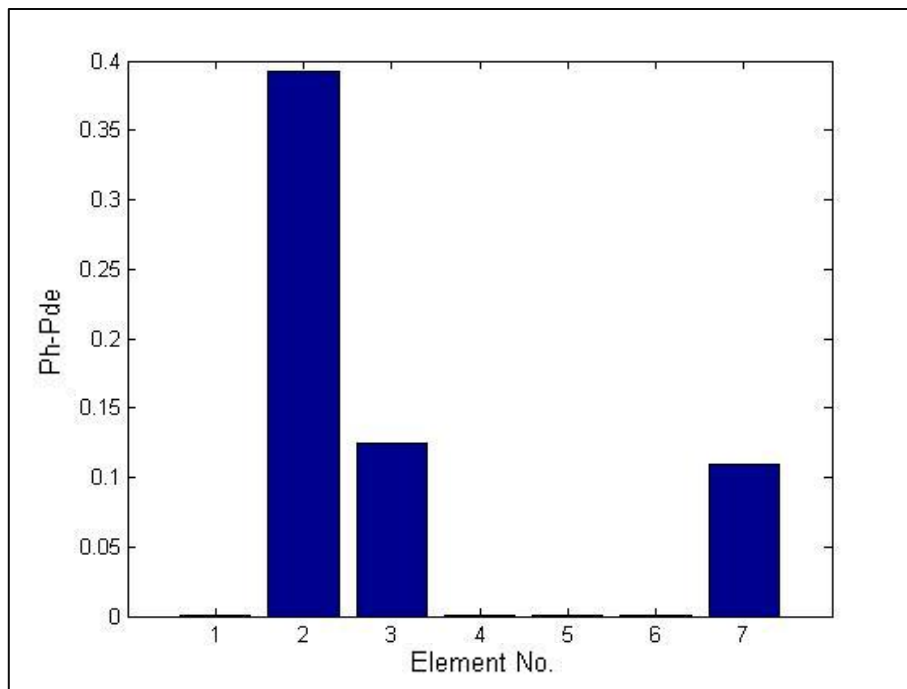


Figure (4.2-b): Second member simulated damage

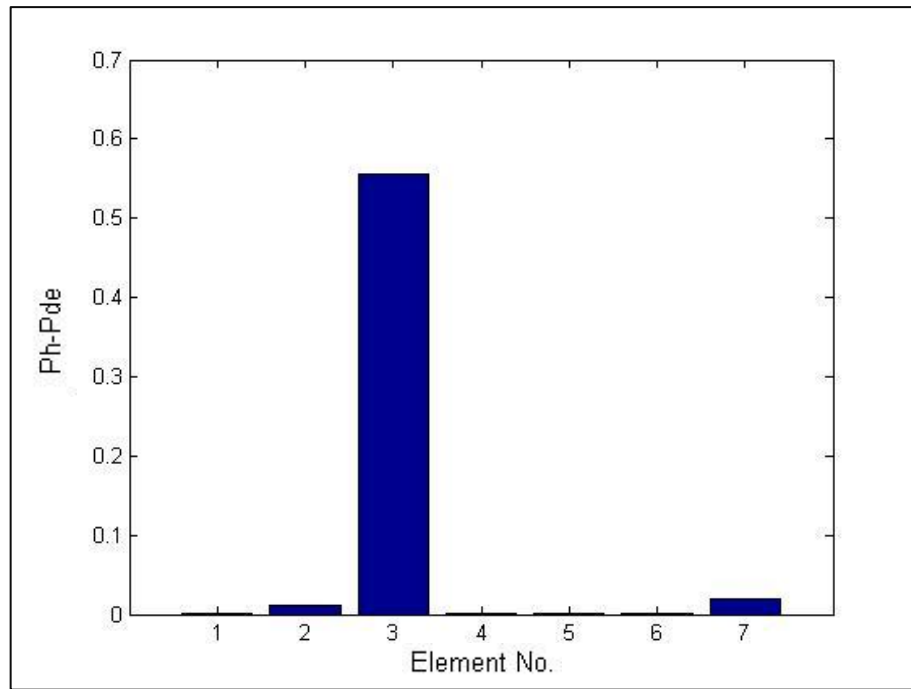


Figure (4.2-c): Third member simulated damage

As shown in Fig.(4.2-b&c) when damage was induced on the second and third element the best sensor configuration collected through the algorithm was [1110001] and [0110001] respectively and it is clear from the figures that the algorithm caught the damage location and extent correctly.

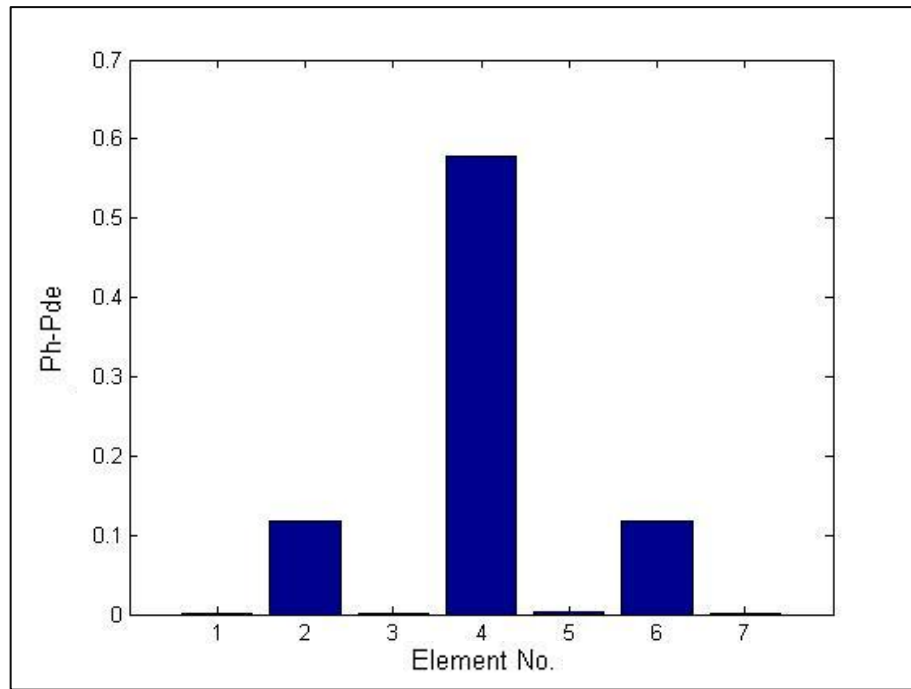


Figure (4.2-d): Middle member simulated damage

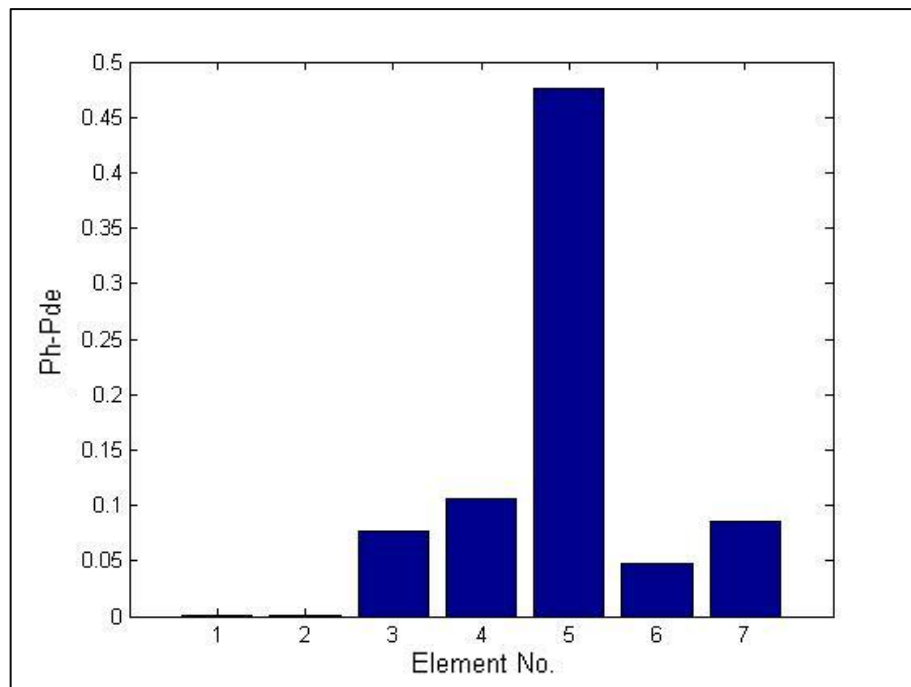


Figure (4.2-e): Fifth member simulated damage

Referring to table (4.1) it could be seen that when damage was induced to the fourth and fifth elements more sensors were required to detect damage in both location

and extent, and both scenarios had the same sensor configuration [1111110], where the percentage of error between the healthy and damaged case was (16-18%), this could be due to the fact that there is a motionless nodal point in the beam's higher modes of vibration, consequently there will be some lost data at that node, Figures (4.2-d,e) depicts the damaged members results.

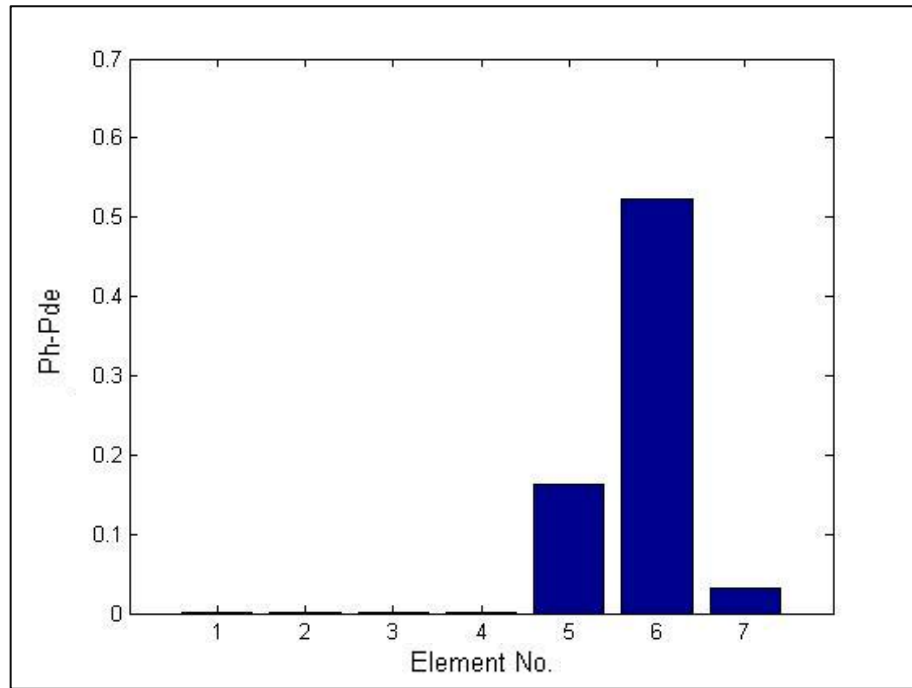


Figure (4.2-f): Sixth member simulated damage

Figure (4.2-f) verifies that the sensor placement configuration collected by the PSO algorithm in the case of damage induced on the sixth element of the beam was [1101111], which by this configuration the LMI damage detection algorithm was able to detect damage location and extent adequately.

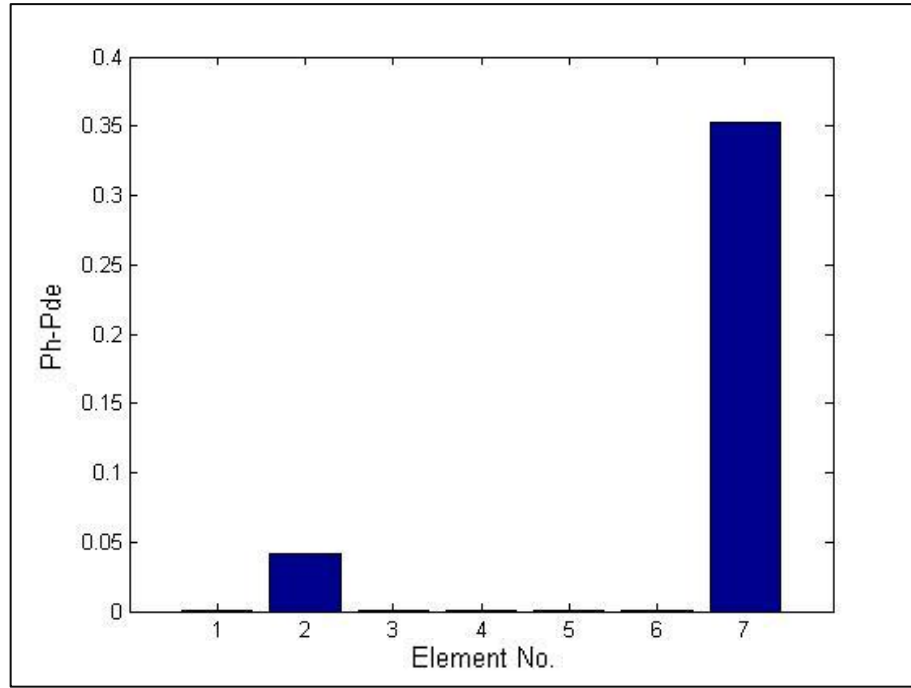


Figure (4.2-g): Tip member simulated damage

A more challenging case is to consider the damage to be on the beam's tip element. In this damage scenario the damaged element is a part from the root, which reflects less strain energy. Assuming a 50% loss of stiffness on the last beam's member dictates to use a [0010001] sensor configuration according to the PSO sensor placement algorithm. This sensor placement is verified and the damage detection algorithm found the location and extent successfully as shown in Fig. (4.2-g).

However the result for the proposed sensor placement scenarios in the case of single damage seems to be nicely working since both the location and damage extent were fully verified.

4.2.2 Multi-Damage Results

Simulation results for multi damage scenarios are shown in table (4.2). Damage was applied to two elements in each case, where damage was induced on the first element with combination with the rest sixth elements. The other case is when damage

is induced to three elements at once, the first two elements with combination of the rest five elements. The final two items in the table represent the case when damage is induced to all elements but the first case was with full measurement data and the last one is with partially measurement data.

Table (4.2): Multi- Damage Sensor Configuration

	Damaged Element	Error (%) (Fitness_Gbest) $\ Pd - Pde\ \times 100\%$	Decimal Sensor Configuration (Gbest)	Number of sensors used	Binary Sensor Configuration
1.	First & Second	28.72	114	4	[1 1 1 0 0 1 0]
2.	First & Third	19.60	126	6	[1 1 1 1 1 1 0]
3.	First & Fourth	40.87	54	4	[0 1 1 0 1 1 0]
4.	First & Fifth	39.00	74	3	[1 0 0 1 0 1 0]
5.	First & Sixth	41.97	109	5	[1 1 0 1 1 0 1]
6.	First & Seventh	42.58	94	5	[1 0 1 1 1 1 0]
7.	First, Second & Third	41.24	126	6	[1 1 1 1 1 1 0]
8.	First, Second & Fourth	44.26	125	6	[1 1 1 1 1 0 1]
9.	First, Second & Fifth	47.03	126	6	[1 1 1 1 1 1 0]
10.	First, Second & Sixth	34.96	100	3	[1 1 0 0 1 0 0]
11.	First, Second & Tip	45.26	107	5	[1 1 0 1 0 1 1]
12.	All elements	37.77	127	7	[1 1 1 1 1 1 1]
13.	All elements	96.33	126	6	[1 1 1 1 1 1 0]

Multiple damage scenarios are also possible. Consider damage on two beam elements at once, with 50% loss of stiffness on each. In every case, damage was applied to the first element with a combination of the other six elements. It was found that as the second damage is part away from the root, the proposed algorithm will still be able to detect damage correctly but with higher percentage of error. Scanning the result, one could sight that a sensor on the first element is a must, while the majority of cases showed that no sensors on the tip element is necessary. The simulation results for all damage scenarios are shown in figures (4.3-a-f).

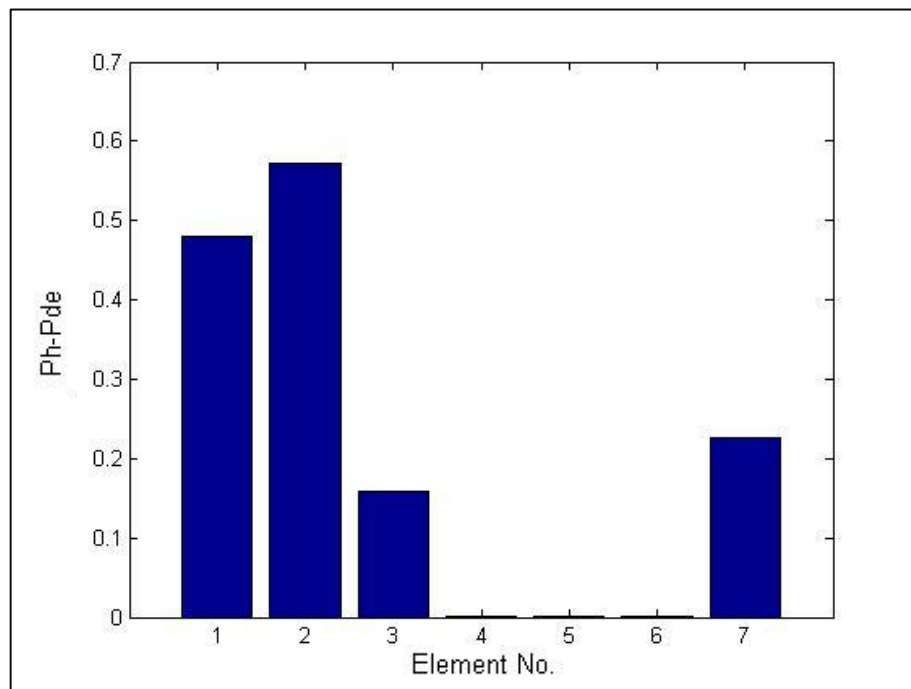


Figure (4.3-a) Damage on the first two members

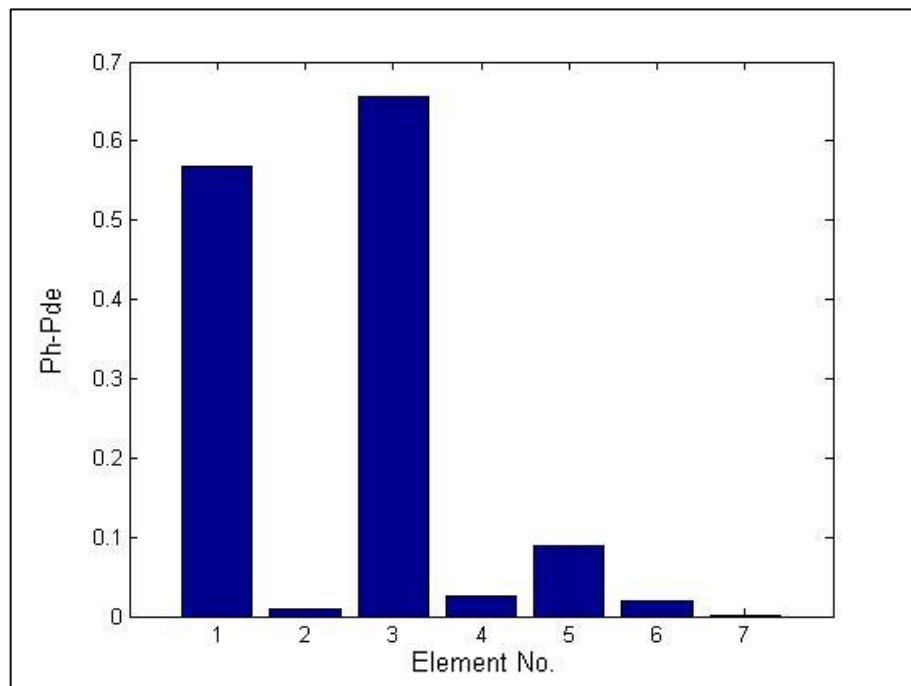


Figure (4.3-b) Damage on the first and third member

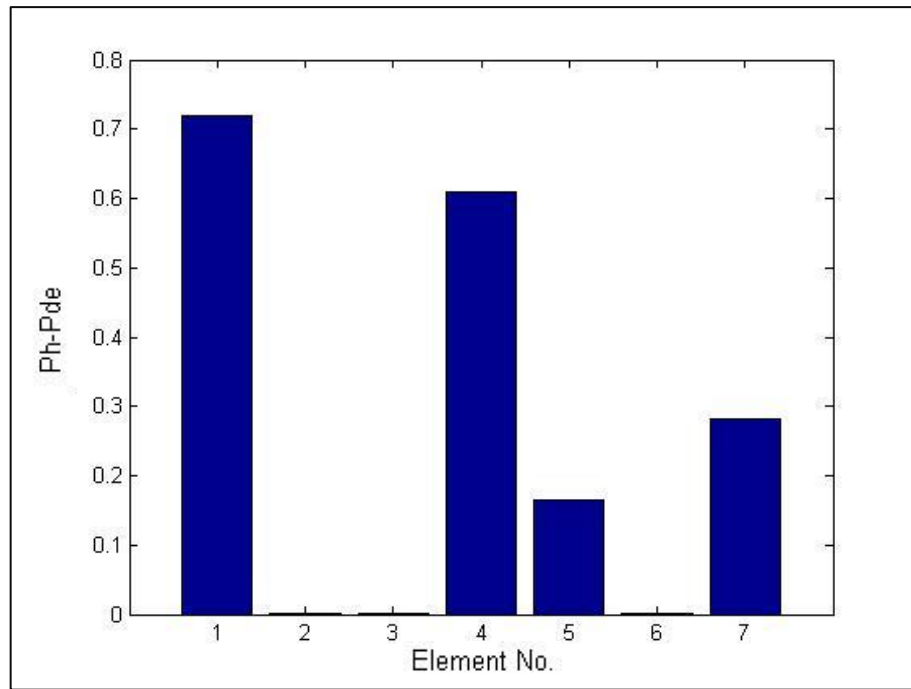


Figure (4.3-c): Damage on the first and fourth member

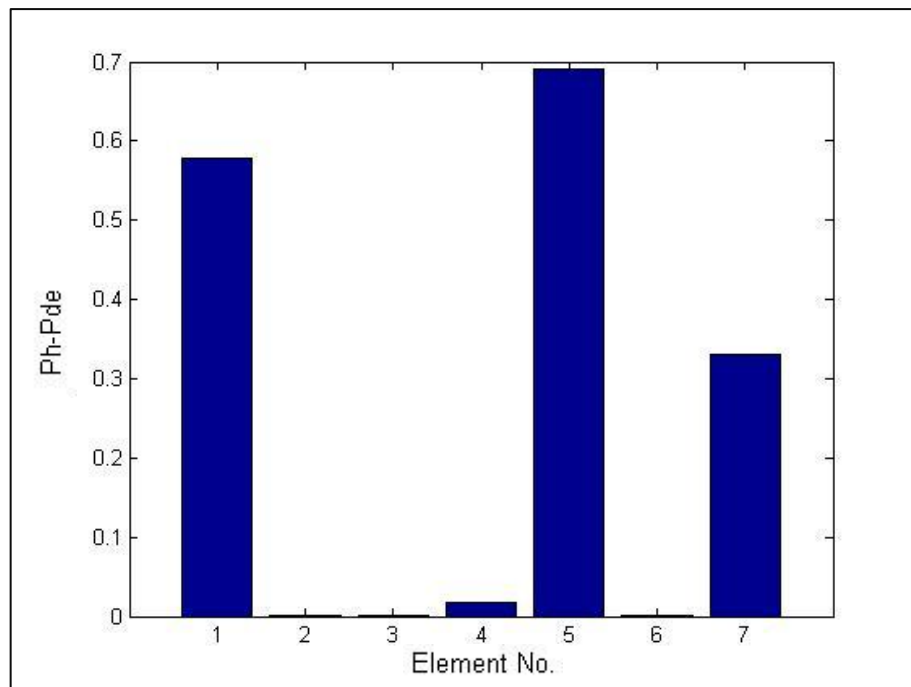


Figure (4.3-d): Damage on the first and fifth member

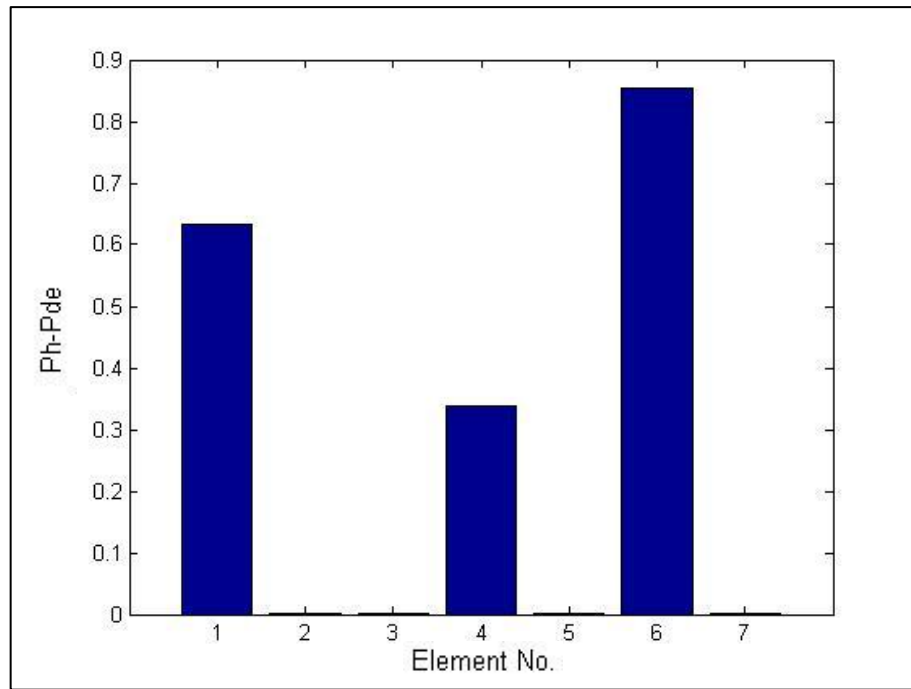


Figure (4.3-e): Damage on the first and sixth members

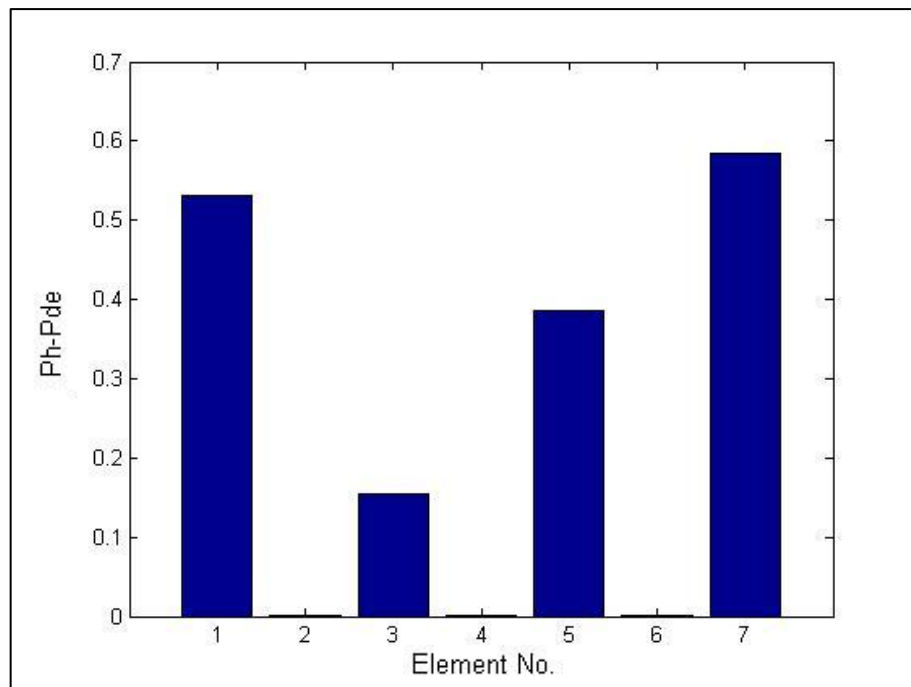


Figure (4.3-f): Damage on the first and Seventh member

Another multi damage scenario's was held, but this time damage was induced at three elements at once. In this case more sensors are required to detect damage, where

most cases required at least five sensors, the error in detecting both location and extent ranges (35-45%), for instant, in the case damage was induced on the beams' elements 1, 2 and 3, 1, 2 and 4 and finally 1, 2 and 6 with loss of member's stiffness's of 50%. The best sensor placement configuration for this multi-damage problem is [1111110], [1111101] and [1100100] respectively. Verifying these sensor locations by executing the LMI detection scheme produces the results depicted in Fig.(4.4-a,b&d) shown below. Clearly, the PSO's suggested sensor configuration provided adequate information for the damage scheme.

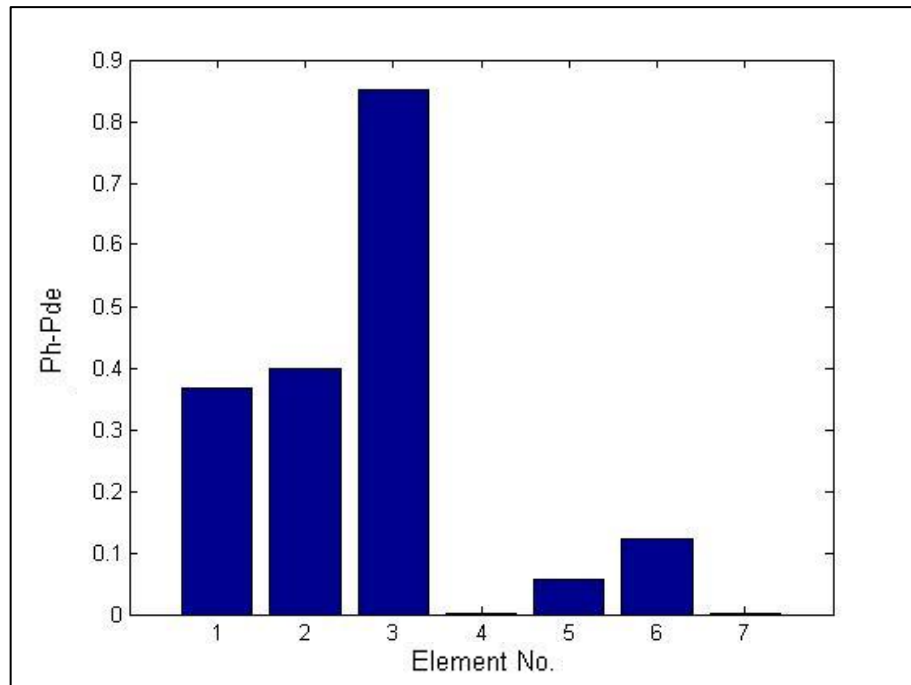


Figure (4.4-a): Damage on the first, second and third members

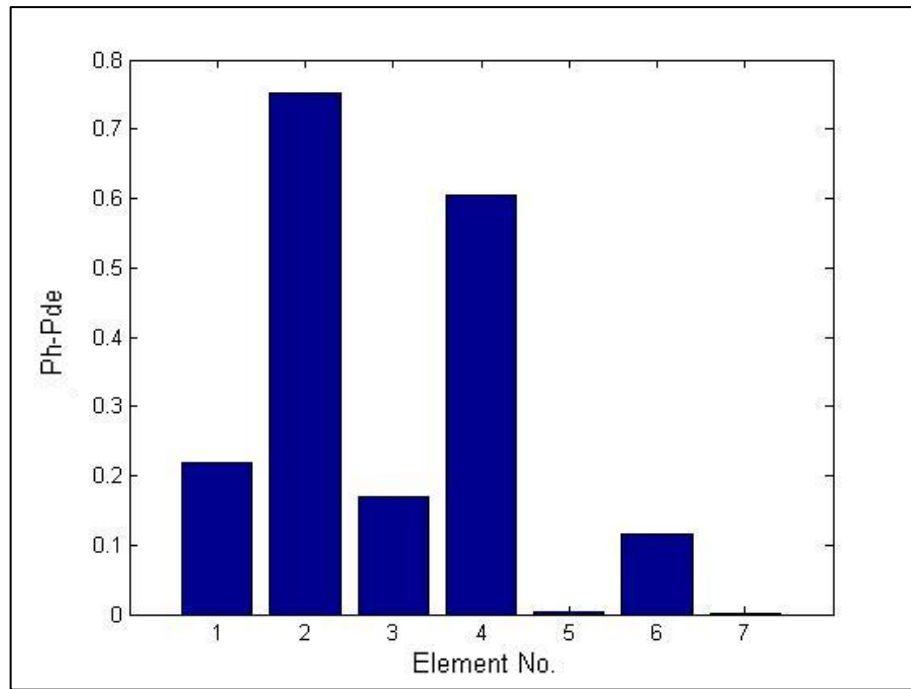


Figure (4.4-b): Damage on the first, second and fourth members

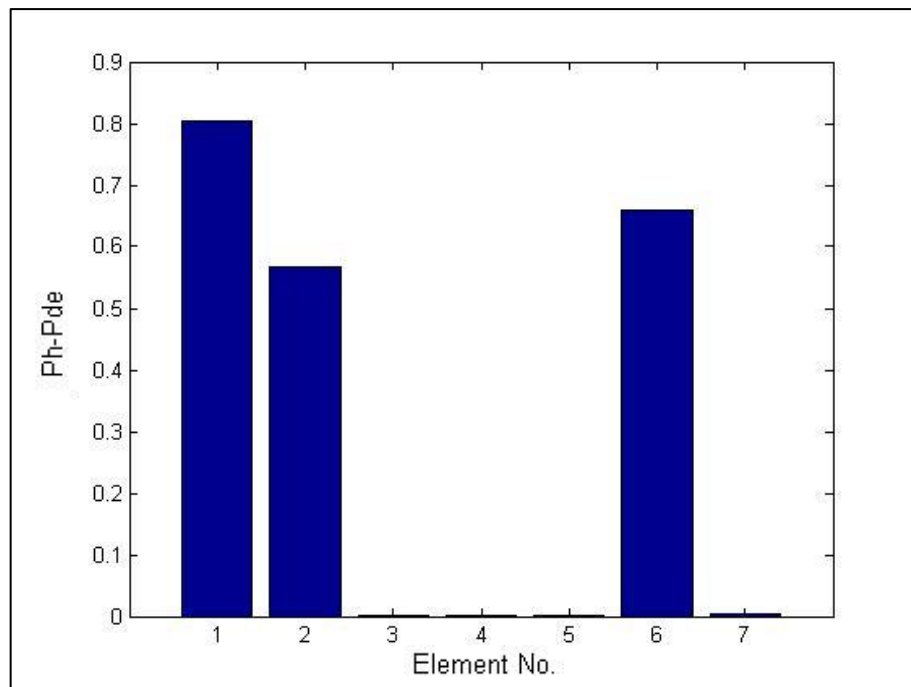


Figure (4.4-d): Damage on the first, second and Sixth members

It could be noted that in the case damage was applied to elements 1, 2 and 5 and 1, 2 and 7, although the algorithm was able to detect damage location correctly and the

extent with a small error with a sensor configuration of [1111110] and [1101011] respectively, but by referring to Fig.(4.4-c,e) damage on element 4 and 5 respectively could be seen, this damage is due to the buildup noise, where this noise was produced as a kind of damage on non-damaged element. Still the PSO suggested sensor configuration's was able to detect damage location adequately and the extent of damage with (40%) average percentage of error.

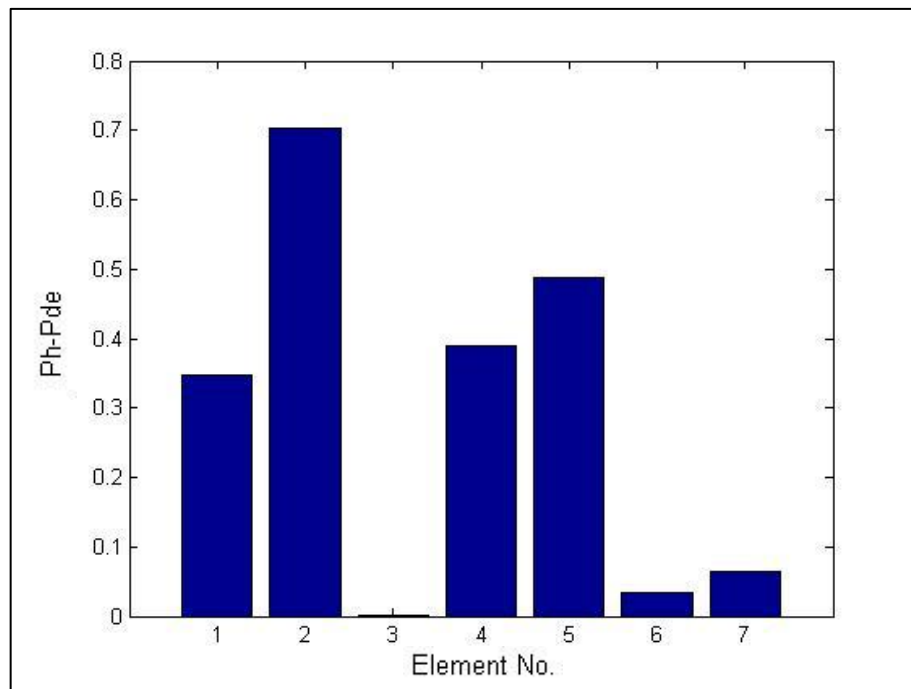


Figure (4.4-c): Damage on the first, second and fifth members

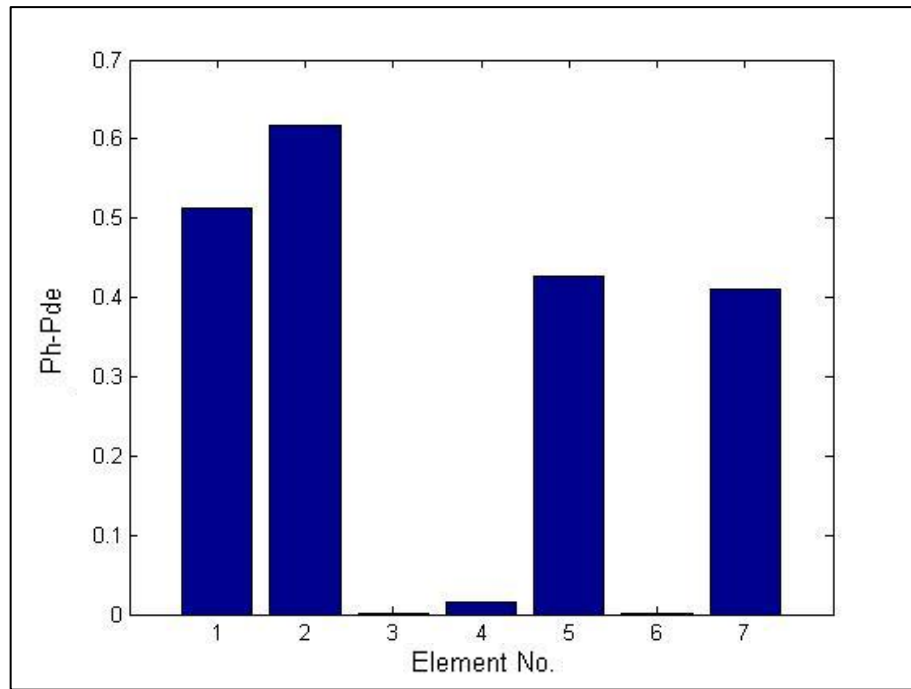


Figure (4.4-e): Damage on the first, second and Seventh members

Two different runs of the algorithm were done for a special scenario with (50%) loss of stiffness on all beam's members. One run was using the full measurement data where the other was using partial measurements. Off course the algorithm was able to provide precise information about damage for both location and extent in the case of full measurements, where it was only able to locate damage adequately but the extent had problems on different elements of the beam, the PSO suggested sensor configuration for this case was [1111110] and Fig.(4.5-a,b) clarifies the difference in both cases.

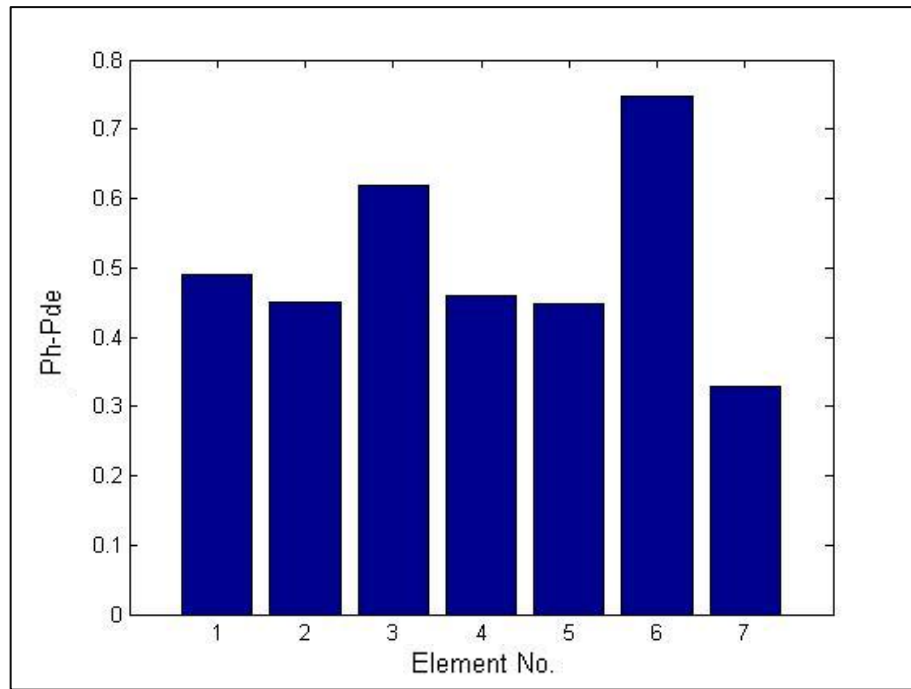


Figure (4.5-a): Damage on all members with full measurements

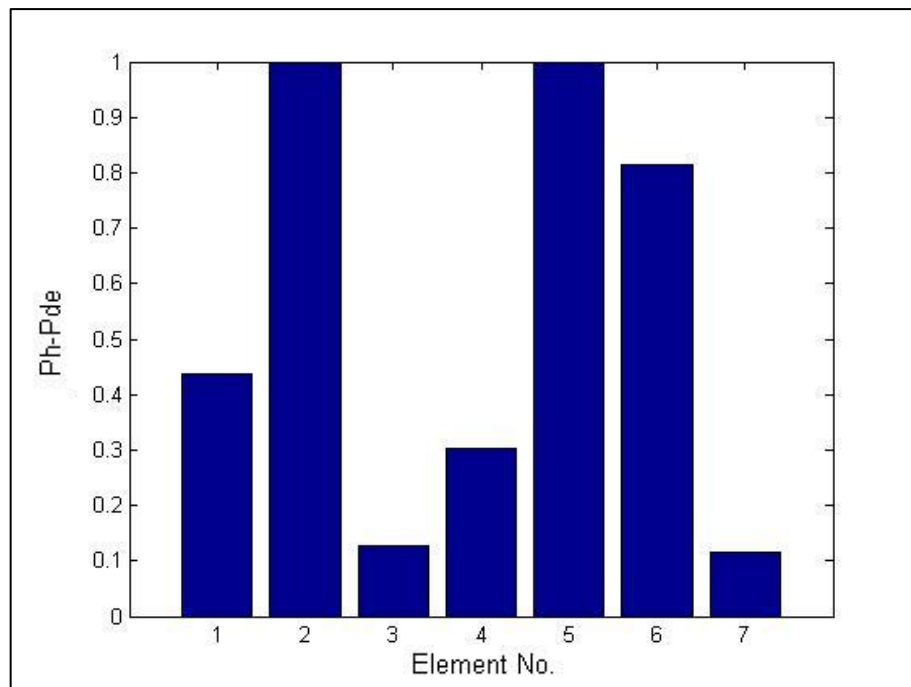


Figure (4.5-b): Damage on all members with partial measurements

This damage scenario is out of the research objective, where the objective was to give alarming of damage at early stages of damage not when all elements are damaged

with 50% loss of stiffness which is considered as a sever case, but we introduced it as prove that the algorithm could still give satisfactory information about damage.

4.3 Simulated Results Validation

Sensor placement for damage detection problems has attracted many researchers and engineers in literature. In this section, a brief overview of these techniques is presented to shed the light on some of popular techniques. The PSO sensor placement technique results will be validated using the Eigenvalue Vector Product (EVP) method.

4.3.1 Popular Techniques

Effective Independence (EFI) was developed to place a certain number of sensors on a structure where these sensors will give best fit to a set of targeted mode shapes. The method depends on maximizing the determinant of the associated Fisher information matrix to maximize both the spatial independence and signal strength of the targeted mode shapes [36, 43].

One limitation of the Effective Independence method was that it could select a sensor location with low energy content, which might lead to a possibility of information loss. Consequently, the Effective Independence Driving Point Residue (EFI-DPR) was developed to overcome this problem by multiplying the candidate sensor contribution of the EFI by the corresponding driving point residue (DPR) coefficient [43].

The main objective of the Kinetic Energy method was to choose the optimal sensor configuration by selecting the location of sensors with the maximum measure of the structures' kinetic energy. The Fisher Information matrix was then weighted with the finite element model mass matrix generating the required kinetic energy matrix [35, 43].

4.3.2 Eigenvalue Vector Product

The eigenvalue vector product (EVP) is an energy based technique that employs a computed spatial vector to place the structure's sensors. EVP is calculated by taking the absolute value of the multiplication of the eigen-vector components over the modes range chosen, or mathematically may be presented by the expression:

$$EVP_i = \prod_{j=1}^N |\Phi_{ij}|$$

This technique selects the sensors with the largest EVP values in order to prevent the choice of sensors placed on nodal lines of a vibration mode, which leads to maximizing their vibration energy [43].

To validate the proposed work, seven different single damage scenarios were chosen and the EVP was applied to the damaged mode shapes matrix. EVP generated sensor configurations were compared with the Particle Swarm Optimization technique using the same number of sensors and the results as presented in table (4.3).

Table 4.3: Sensors' configurations generated by PSO and EVP for single damage scenarios

Damage Scenario	PSO	EVP
Root element	[1110001]	[0011011]
Second element	[1110001]	[0011101]
Third element	[0110001]	[0011001]
Fourth element	[1111110]	[1011111]
Fifth element	[1111110]	[0111111]
Sixth element	[1101111]	[1101111]
Tip element	[0010001]	[0001001]

The EVP sensor configuration was then test using LMI to detect the induced damage scenario, but unfortunately LMI was not able to detect damage in both location and extent using the EVP generated sensor configuration.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

In this work the main objective was to find out sensor configuration on structures that exploits certain selected inflected damage scenarios. This was important in order to aid the used structural health monitoring and damage detection algorithm.

5.1 Conclusions

Sensor placement methodology based on Particle Swarm Optimization (PSO) and Linear Matrix Inequality (LMI) was presented. A cantilevered beam simulation test-bed was used to verify and validate the sensors configuration for the structural health monitoring.

The LMI was successfully used as a damage detection algorithm to test for the optimally generated sensor configuration. Single and multiple damage scenarios were investigated and successfully detected in location and extent.

Partially measured modal data for structures were first treated using the System Equivalent Reduction Expansion Process (SEREP) before implementing the LMI damage detection method. The expansion process generated good results in conjunction with the sensor placement algorithm.

Finally, Particle Swarm Optimization (PSO) was successfully used to search the sensors location solution space, providing optimal configurations that exploits certain damage scenarios (hot spots).

5.2 Future Work and Recommendations

A practical implementation of a cantilevered beam experiment would complement this work and it will provide a good verification and validation for the effectiveness of the proposed method.

Uncompensated for parameters such as measurement of noise, un-modeled dynamics, non-exact geometry (uncertainties) will be a good challenging test for the algorithm.

The algorithm could be enhanced to provide a unique sensor configuration to supply the user with adequate information about damage (location and extent) for any scenario by a precise tuning of the LMI damage detection algorithm parameters. Even though the sensor placement proposed method utilizes Linear Matrix “Inequalities (LMI) for the damage detection process but other methods are also possible such as using Fuzzy logic, Neural Networks, MRPT ...etc.

The minimum rank perturbation theory (MRPT) was successfully tested on a truss member by researchers, but in the case of the cantilevered beam it did not give satisfactory results, so the method was successfully implemented to optimally place some sensors for truss structure, but it is recommended testing this sensor placement method on more complex structures such as a truss using different damage detection algorithms to validate and verify these preliminary findings.

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APPENDIX A

The mass and stiffness matrix of the healthy cantilevered beam are shown below:

$M_h =$

0.1759	0	0.0285	-0.0009	0	0	0	0	0	0	0	0	0	0
0	0.0001	0.0009	0	0	0	0	0	0	0	0	0	0	0
0.0285	0.0009	0.1759	0	0.0285	-0.0009	0	0	0	0	0	0	0	0
-0.0009	0	0.0001	0.0009	0	0	0	0	0	0	0	0	0	0
0	0	0.0285	0.0009	0.1759	0	0.0285	-0.0009	0	0	0	0	0	0
0	0	-0.0009	0	0	0.0001	0.0009	0	0	0	0	0	0	0
0	0	0	0	0.0285	0.0009	0.1759	0	0.0285	-0.0009	0	0	0	0
0	0	0	0	-0.0009	0	0	0.0001	0.0009	0	0	0	0	0
0	0	0	0	0	0	0.0285	0.0009	0.1759	0	0.0285	-0.0009	0	0
0	0	0	0	0	0	-0.0009	0	0	0.0001	0.0009	0	0	0
0	0	0	0	0	0	0	0	0.0285	0.0009	0.1834	0.0003	0.0311	-0.001
0	0	0	0	0	0	0	0	-0.0009	0	0.0003	0.0001	0.001	0
0	0	0	0	0	0	0	0	0	0	0.0311	0.001	0.0954	-0.0018
0	0	0	0	0	0	0	0	0	0	-0.001	0	-0.0018	0

$$K_h = 1e^6 \times$$

7.0104	0	-3.5052	0.2226	0	0	0	0	0	0	0	0	0	0
0	0.0377	-0.2226	0.0094	0	0	0	0	0	0	0	0	0	0
-3.5052	-0.2226	7.0104	0	-3.5052	0.2226	0	0	0	0	0	0	0	0
0.2226	0.0094	0	0.0377	-0.2226	0.0094	0	0	0	0	0	0	0	0
0	0	-3.5052	-0.2226	7.0104	0	-3.5052	0.2226	0	0	0	0	0	0
0	0	0.2226	0.0094	0	0.0377	-0.2226	0.0094	0	0	0	0	0	0
0	0	0	0	-3.5052	-0.2226	7.0104	0	-3.5052	0.2226	0	0	0	0
0	0	0	0	0.2226	0.0094	0	0.0377	-0.2226	0.0094	0	0	0	0
0	0	0	0	0	0	-3.5052	-0.2226	7.0104	0	-3.5052	0.2226	0	0
0	0	0	0	0	0	0.2226	0.0094	0	0.0377	-0.2226	0.0094	0	0
0	0	0	0	0	0	0	0	-3.5052	-0.2226	6.2119	-0.0352	-2.7067	0.1873
0	0	0	0	0	0	0	0	0.2226	0.0094	-0.0352	0.0361	-0.1873	0.0086
0	0	0	0	0	0	0	0	0	0	-2.7067	-0.1873	2.7067	-0.1873
0	0	0	0	0	0	0	0	0	0	0.1873	0.0086	-0.1873	0.0173

تحديد مواقع المجسات لتحسين عملية الكشف عن الأضرار الناتجة عن التغيير في

صلبية المواد

إعداد

إيناس محمد الخوالده

المشرف

الدكتور جهاد يامين

المشرف المشارك

الدكتور موسى عبدالله

الملخص

تقدم الدراسة طريقة للاختيار الأمثل لمواقع و أعداد المجسات التي يمكن استخدامها للكشف عن العديد من سيناريوهات الأضرار التي قد تقع على المباني و الهياكل. تستخدم النظرية طريقة بحث باستخدام النظام الثنائي معتمدة على نظرية سرب الجسيمات الأمثل والذي يرمز له (PSO) لإيجاد أفضل توزيع لأماكن و اعداد المجسات، كما و تطبق نظرية عدم مساواة المصفوفات الخطية والتي يرمز لها (LMI) لإيجاد أماكن و قيم الأضرار الواقعة. وتتعامل هذه الدراسة مع القياسات الجزئية لاهتزازات المبنى أو الهيكل، وبالاعتماد على نظرية مكافئة الانظمة من خلال عمليات حد و توسيع القياسات والتي يرمز لها (SEREP) يمكن إعادة احتساب هذه القياسات بحيث تحوي كامل القراءات عن معلومات اهتزاز المبنى أو الهيكل. كما و تم التحقق بنجاح من صحة النتائج وفعاليتها من خلال تطبيق النظرية على عارضة معلق تعليقاً حر.